# A Fuzzy Decision Making Model for Determining Company Profile in Allocation of Public Funding for Industrial Development Projects

MIGUEL D. ALFARO, JUAN M. SEPÚLVEDA, CARLO A. CASORZO
Department of Industrial Engineering
University of Santiago of Chile
3769 Ecuador Ave. Santiago, Chile. PO Box 10233

*Abstract:* - In this article, a model for classifying companies according to size measures is presented along with an application to Chilean industry. Current variables, such as Yearly Net Sales, Number of Workers, and Total Assets, as well as current classification sets, namely Micro-enterprise, Small and Medium - Enterprise (SME), and Large-Enterprise, are used. The model was applied on a sample of 330 companies and the results show differences with current classification methods used by a public agency in charge of funding industrial development and research projects. By validating the model against the outcomes of current decision making, a better public's perception of a right classification decision for allocating funds was obtained. A fuzzy logic classification model of this kind may useful for allocating funds either to companies or individuals when traditional crisp numbers and criteria are difficult to handle.

*Key-Words:* - Fuzzy logic, Fuzzy classification, Company profile.

## 1 Introduction

The use of fuzzy logic (FL) for classification processes has been applied in several domains and to a great variety of problems. In [6], authors used FL for classifying product quality characteristics in chemical engineering systems; in [4] FL was applied in the classification of consumers of imported fruit in China, measuring their consumption values; a fuzzy rule-based classification model to define soil quality based on soil microbial biomass, N-mineralization, enzyme activity data and soil organic matter was proposed in [5]; in [3], authors used FL to create a new algorithm to extract sets of rules from data for classification problems; in [7], authors used FL for selecting different cotton types, among others. In this paper, we use fuzzy logic for classifying companies according to *some measure of size*. In the introducing section, the problem to be solved and common different criteria for measuring the size of a company are presented. Next the linguistic variables with their corresponding fuzzy sets and an application to the industrial sector are discussed; finally, results and conclusions are presented.

The interest for a company classification model arises from the lack of a unique criterion. That is, an adequate variable and the limits for that variable must be determined for each segment of companies. Besides, the size of a company is a classic variable used in economics for designing development policies and for allocating funds according to an economic profile.

In the region where the study is conducted, there are several public programs for helping companies with their technological development; the objectives and funding of these programs depend on the type of applying company. Currently, the classification method considers some variable: most used are net sales and number of workers. As an example, a company with 249 workers is classified as Medium size and if it has 250 is considered as Large. As seen, the crisp current method may be questionable and it can be even more complicated when another variable must be used. From the public's viewpoint, unsatisfaction and criticism arise towards the public agency since for a marginal change in some variable, a significant decrease, if nothing at all, in funding for projects can be obtained.

In the literature, different definitions for determining the size of a company can be found. The most commonly used variables are the number of workers, fixed asset investment, sales, among others. In the country, only the sales level is considered but there have been many cases where this criterion has proved to be inconvenient for allocating resources, especially in new small fast growing high-tech based companies searching for seed capital.

In this article, the use of fuzzy logic as a tool for classifying companies is presented. That is, a *fuzzy linguistic model* (FLM) including several criteria for determining company size is developed.

For classification problems, fuzzy logic is a mapping process from an input space onto an output space by using membership functions and linguistic rules. Thus, the degree of membership of an element to a class is expressed by a number in the interval [0,1] as opposed to crisp measures where the membership is a dichotomic measure.

The remainder of this paper is organized as follows. In Section 2, a full description of the fuzzy model used is given, including the classification variables, the fuzzification process, the statement of the decision rules and the defuzzification process. The implementation details of the model are shown in Section. Conclusions are given in Section 4.

## 2 Fuzzy Model Description

### 2.1 Classification Variables

In order to define the size of a company, several variables such as fixed capital, sales level, profitability, number of workers, among others, can be used. In this work, we use variables currently used by the Chilean Corporation for Industrial Development (CORFO), a public state agency in charge of promoting industrial development in the country, specially focused on SMEs. Also we use other variables that have been suggested in the literature [1]. Variables in use by the corporation are net yearly sales, number of workers, and total assets. The classification, according to these variables by separate, is shown in Table 1.

| SIZE | SALES (UF)[1] | WORKERS | ASSETS (UF) |
|---|---|---|---|
| MICRO | Up to 2,400 | Up to 10 | Up to 38,000 |
| SME | 2,401 to 100,000 | 11 to 200 | 38,001 to 380,000 |
| LARGE | Over 100,000 | Over 200 | Over 380,000 |

Table 1. *Classification of companies according to size for developing the model*

For the FLM, three fuzzy sets for the input variables have been selected. For *yearly net sales*, fuzzy sets are *low, normal and high*. For *number of workers*, the corresponding sets are *few, normal, and many*. For *total assets*, the fuzzy sets are *low, normal, high*.

By using the FLM, a classification for the main three classes of company sizes can be obtained. These classes will be the output set of the model: *micro, small and medium, and large enterprise*.

Once the fuzzy sets are chosen, the membership function for each of them must be established. The membership function maps an input element onto a value in [0,1] thus showing the level of membership to the fuzzy set. The shape of the function should be elicited from the decision makers(s) and can be gaussian, sinusoidal, triangular, or trapezoidal type. In this work, without loss of generality, we use the trapezoidal type for the simplicity of establishing membership values when asking decision makers (DM). That is, DMs feel comfortable with *linear thinking* as variables get closer or further from the ideal region.

A trapezoidal membership function is specified by four parameters {a, b, c, d} as shown in Fig. 1 and its expression in Equation 1.

The procedure for determining the parameters of the membership function is the same for each of the selected variables. Next, an example for the case of *Yearly Net Sales* variable and fuzzy sets: *low, normal, and high*, is given.

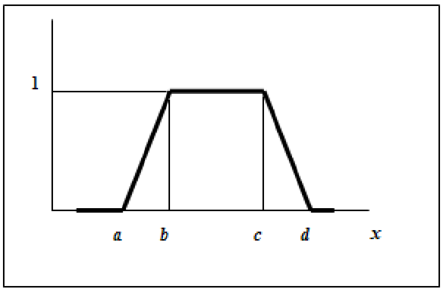

Fig. 1. *Trapezoidal membership function.*

$$f(x;a,b,c,d) = \max\left\{\min\left(\frac{x-a}{b-a},1,\frac{d-x}{d-c}\right),0\right\}. \quad (1)$$

***Step 1***: the current classification scheme used by CORFO, which is based on dichotomical reasoning (Table 1), defines sharp values for the classes. In this work, these values are defined as the intersections between the different fuzzy sets of the variable as shown in Fig. 2.

***Step 2***: in order to obtain parameters *a* and *b*, the distance between each sales level and the 2,400 UF level is calculated. For the *a* parameter, only the sales values of those companies currently classified as *micro* are taken. Then, a range where *micro* enterprises are considered to be close to *small and medium* is defined. Thus a value of *a* equal to 2,363 UF is determined. Finally, the parameter *b* value is 2,437 UF due to the symmetrical property of the trapezoidal function.

***Step 3***: in order to obtain parameters *c* and *d*, the distance between each sales level and the 100,000 UF level is calculated. Next we proceed the same way as in *Step 2*. Thus, the value of *c* is 90,340 UF and the value of *d* is 109,660 UF. Table 2 summarizes the results of this process for each variable.

In Fig. 2 the membership function for the *Sales* variable and its corresponding fuzzy sets are

[1] UF (Unidad de Fomento) is an inflation-free parity index, where 1 UF is aproximately USD 35.85 (August 2007).

presented. For the other variables, the same procedure is followed.

| Variables | Parameters | | | |
|---|---|---|---|---|
| | *a* | *b* | *c* | *d* |
| Yearly Net Sales (UF) | 2,363 | 2,437 | 90,340 | 109,660 |
| N° of Workers | 12 | 50 | 160 | 440 |
| Total Assets (UF) | 36,746 | 40,652 | 320,125 | 412,052 |

Table 2. *Parameter values of fuzzy sets for each input variable.*

## 2.2 Fuzzification

Fuzzification is referred as to the modeling stage where we determine the range to which a sample of input data belongs to for each fuzzy set, by using the membership function. For a known input vector defined as: $E_0$ = ($Sales_0$, $Workers_0$, $Assets_0$), the membership values must be calculated for all fuzzy sets associated with each linguistic variable. For example, if $E_0$ = (17,115; 219; 288,173) a *sales* level of 17,115 UF has a membership value of 1 in the fuzzy set *normal* , a *number of workers* level of 219 has a membership value of 0.78 in the fuzzy set *normal* and of 0.22 in the fuzzy set *many*. Last, a *total assets* level of 288,173 UF has a membership value of 1 in the fuzzy set *normal*. Next, it follows the *defuzzification* stage in order to obtain the degree of membership of the output sets: *micro, small and medium, and large enterprise.* For this, decision rules construction is needed.

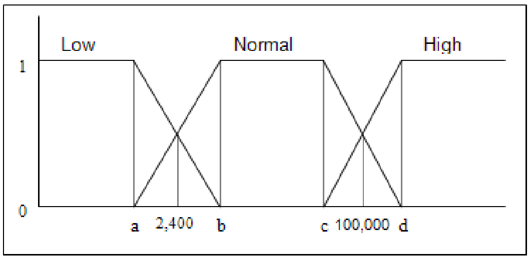


Fig. 2. *Fuzzy sets for Sales variable.*

## 2.3 Decision Rules

In a fuzzy linguistic model, decision rules give reasoning qualities for chaining fuzzy input sets with fuzzy output sets. These rules correspond to a collection of linguistic production rules well known in the expert systems area of artificial intelligence. As an example, a typical rule can be as follows:

IF *Sales* is *high* AND *Number of Workers* is *normal* AND *Total Assets* is *high*
THEN *Size* is *large*.

The use of fuzzy operators is necessary in order to specify the relationship between the fuzzy output sets with the rule's *antecedent* (left hand side). Most common operators, as the ones shown in the example, are the *OR* operator representing set union and the *AND* operator representing set intersection. Also the *NOT* operator which represents the complement set. In the example above, the intersection of all sets is needed in order to fire the rule, as shown in equation 2.

$$A \text{ and } B \text{ and } C = \min\{\mu_A(x), \mu_B(x), \mu_C(x)\}. \quad (2)$$

Where $\mu_A(x)$, $\mu_B(x)$, $\mu_C(x)$ are the membership values of the sets A, B and C respectively, which have been obtained from the trapezoidal membership functions defined earlier. The *min* value corresponds to the degree of compliance of each linguistic rule. For example, in the rule,

IF *Sales* is *normal* AND *Number of Workers* is *normal* AND *Total Assets* is *normal*
THEN *Size* is *large,*

The degree of compliance is 0.78. The linguistic rules must be established from existing knowledge about company classification by size. As there are three fuzzy sets for the *Sales* variable, three for *Number of Workers*, and three for *Total Assets*, there will be 27 possible combinations for the rule antecedents. In our case, the rules were established by experts of CORFO, the public agency in charge of industry development in Chile which depends on the Economics Ministry. These rules are presented in a tabular form in Appendix 1.

## 2.4 Defuzzification

For a given company, there may be more than two linguistic rules with different *consequences* since the value of an input variable may fall into the fuzzy interval leading to two different conditions. To avoid this problem, we need a *Defuzzification* mechanism in order to obtain a unique size. In this work, the *max method* is used. That is, the rule with the highest degree of compliance among all possible firings is then chosen in order to generate exactly one company size.

| SIZE | CRITERIA | | |
|---|---|---|---|
| | Sales | Nº of Workers | Total Assets |
| MICRO | 15 | 62 | 11 |
| SME | 245 | 249 | 76 |
| LARGE | 70 | 19 | 243 |
| TOTAL | 330 | 330 | 330 |

Table 3. *Current number of companies per class (Source: CORFO 2007).*

In Table 3 the number of classified companies (330 in total) by using current agency criteria is shown. As seen, the size class can significantly differ when different criteria are used. For example, if we consider *number of workers*, 62 companies are *micro* size whereas by *Total* Assets are 11 companies and by *Sales is 15.* The same happens with *Large* size where the number of companies is 70 if *Sales* is considered, 19 if *Number of Workers* is considered, and 243 if *Total Assets* is used. One practical consequence of such an inconsistency is wrong classification and allocation of public resources.

## 3 Implementation

The model was programmed with Visual Basic 6.0 ™ and Access 2003 ™ for the database with 330 industrial companies. Results are summarized in Table 4.

| Degree of membership | MICRO | SME | LARGE |
|---|---|---|---|
| 0.500-0.700 | 1 | 7 | 23 |
| 0.701-0.999 | 3 | 9 | 24 |
| 1.000 | 11 | 38 | 214 |
| *Subtotal* | 15 | 54 | 261 |
| **Total** | | 330 | |

Table 4. *Summary of results by using fuzzy the classification model.*

It can be observed that with a degree of membership higher than 0.5, a number of 15 companies are classified as *Micro*, 54 companies as *SME* and 261 as *Large*. In order to determine the degree of similarity between classification schemes by using variables separately and the classification obtained by the fuzzy model, we calculated the number of companies that coincide with its class by using *euclidean distance*. In the first case, we obtained 139, 43, and 308 coincidences according to the Sales, *Number of Workers*, and *Total Assets* criteria, respectively. By using *euclidean distances*, we obtained the distances 270, 314, 37 with respect to criteria *Sales*, *Number of Workers*, and *Total Assets* respectively. It is concluded that *Total Assets* is the current variable that approximates the most to the model-based classification. On the other hand, the variable *Number of Workers* is the one that differs most from the model results. In Appendix 2, the obtained results are shown. Because of a matter of space, only the first 48 results are shown, from a total of 330 results.

## 4 Conclusions

Determining the size of a company is a difficult task due to the arbitrary definition of ranges for the size as well as for the variables used in the classification. The method used in this work solves the range problem and it allows for the integration of different variables considered to be important to the classification task. The values used in the work are actual for the context problem presented here but it is believed the method may be useful in many other situations dealing with multicriteria classification. In large decision problems, with many variables and values, expert systems type of decision support may be used. For the particular application of this work, *Total Assets* is the current criteria which best resembles the fuzzy model classification.

*References:*


[1] L. Boedo and A. Calo, Incidencia del Tamaño Sobre el Comportamiento Financiero de la Empresa: Un Análisis Empírico con Pymes Gallegas, *Revista Gallega de Economía*, Vol. 10, 2001, pp. 1-23.

[2] European Commision, *The European Observatory for SME*, Sixth Report, Luxemburg: Office for Official Publications of the European Communities, 2000.

[3] R. Irrizarry, Fuzzy Classification With an Artificial Chemical Process, *Chemical Engineering Science,* Vol. 60, No. 2, 2007, pp. 399-412.

[4] X. Sun and R. Collins, The Application of Fuzzy Logic in Measuring Consumption Values: Using Data of Chinese Consumers Buying Imported Fruit, *Food Quality and Preference*, Vol. 18, No. 3, 2007, pp. 576-584.

[5] D. Tscherko, E. Kandeler and A. Bárdossy, Fuzzy Classification of Microbial Biomass and Enzyme Activities in Grassland Soils, *Soil Biology and Biochemistry*, Vol. 39, No. 7, 2007, pp. 1799-1808.

[6] G. Tsekouras, H. Sarimveis, R. Costas and G. Bafas, A Fuzzy Logic Approach for the Classification of Product Qualitative Characteristics, *Computers & Chemical Engineering*, Vol. 26, No. 3, 2002, pp. 429-438.

[7] B. Xu, D.S. Dale, Y. Huang and M.D. Watson, Cotton Color Classification by Fuzzy Logic, *Textile Research Journal*, Vol. 72, No. 6, 2002, pp. 504-509.

**APPENDIX 1**
**Matrix of Fuzzy Rules for the Design of the Linguistic Model**

| RULES | ANTECEDENT | | | | | | | | | CONSEQUENT |
|---|---|---|---|---|---|---|---|---|---|---|
| | Sales | | | N° of Workers | | | Total Assets | | | |
| | Low | Normal | High | Few | Normal | Many | Low | Normal | High | Size |
| Rd1 | • | | | • | | | • | | | MICRO |
| Rd2 | • | | | | • | | • | | | MICRO |
| Rd3 | • | | | | | • | • | | | MICRO |
| Rd4 | • | | | • | | | | • | | MICRO |
| Rd5 | • | | | | • | | | • | | MICRO |
| Rd6 | • | | | | | • | | • | | SME |
| Rd7 | • | | | • | | | | | • | SME |
| Rd8 | • | | | | • | | | | • | SME |
| Rd9 | • | | | | | • | | | • | SME |
| Rd10 | | • | | • | | | • | | | MICRO |
| Rd11 | | • | | | • | | • | | | SME |
| Rd12 | | • | | | | • | • | | | SME |
| Rd13 | | • | | • | | | | • | | SME |
| Rd14 | | • | | | • | | | • | | SME |
| Rd15 | | • | | | | • | | • | | SME |
| Rd16 | | • | | • | | | | | • | LARGE |
| Rd17 | | • | | | • | | | | • | LARGE |
| Rd18 | | • | | | | • | | | • | LARGE |
| Rd19 | | | • | • | | | • | | | SME |
| Rd20 | | | • | | • | | • | | | SME |
| Rd21 | | | • | | | • | • | | | SME |
| Rd22 | | | • | • | | | | • | | LARGE |
| Rd23 | | | • | | • | | | • | | LARGE |
| Rd24 | | | • | | | • | | • | | LARGE |
| Rd25 | | | • | • | | | | | • | LARGE |
| Rd26 | | | • | | • | | | | • | LARGE |
| Rd27 | | | • | | | • | | | • | LARGE |

# APPENDIX 1
# The First 48 From a Total of 330 Results Obtained by Using the Fuzzy Model

| Company | Sales | Size by Sales | Assets | Size by Assets | N° of Workers | Size by Workers | Size by Model | Degree | Company | Sales | Size by Sales | Assets | Size by Assets | N° of Workers | Size by Workers | Size by Model | Degree |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Company 1 | 90340 | SME | 1307957 | Large | 55 | SME | LARGE | 1 | Company 72 | 37837 | SME | 620262 | Large | 19 | SME | LARGE | 1 |
| Company 2 | 100065 | Large | 315200 | SME | 262 | Large | LARGE | 0.5034 | Company 73 | 24597 | SME | 408422 | Large | 20 | SME | LARGE | 0.9605 |
| Company 3 | 23092 | SME | 384350 | Large | 12 | SME | LARGE | 0.6987 | Company 74 | 9244 | SME | 162786 | SME | 7 | Micro | SME | 1 |
| Company 4 | 52703 | SME | 858118 | Large | 161 | SME | LARGE | 0.9875 | Company 75 | 35418 | SME | 581562 | Large | 40 | SME | LARGE | 1 |
| Company 5 | 5396 | SME | 101216 | SME | 70 | SME | SME | 1 | Company 76 | 52266 | SME | 851136 | Large | 64 | SME | LARGE | 1 |
| Company 6 | 1111 | Micro | 27778 | Micro | 9 | Micro | MICRO | 0.75 | Company 77 | 86933 | SME | 1253432 | Large | 260 | Large | LARGE | 1 |
| Company 7 | 5289 | SME | 99497 | SME | 92 | SME | SME | 1 | Company 78 | 30110 | SME | 496636 | Large | 57 | SME | LARGE | 1 |
| Company 8 | 25065 | SME | 415917 | Large | 129 | SME | LARGE | 1 | Company 79 | 145684 | Large | 517051 | Large | 170 | SME | LARGE | 0.875 |
| Company 9 | 8496 | SME | 150815 | SME | 27 | SME | SME | 1 | Company 80 | 45128 | SME | 736919 | Large | 33 | SME | LARGE | 1 |
| Company 10 | 6667 | SME | 121542 | SME | 53 | SME | SME | 1 | Company 81 | 69634 | SME | 976649 | Large | 16 | SME | LARGE | 1 |
| Company 11 | 2672 | SME | 57626 | SME | 34 | SME | SME | 1 | Company 82 | 18166 | SME | 305531 | SME | 4 | Micro | SME | 1 |
| Company 12 | 1250 | Micro | 31250 | Micro | 7 | Micro | MICRO | 1 | Company 83 | 244089 | Large | 812267 | Large | 104 | SME | LARGE | 1 |
| Company 13 | 20051 | SME | 335687 | SME | 60 | SME | SME | 0.8307 | Company 84 | 67044 | SME | 935207 | Large | 255 | Large | LARGE | 1 |
| Company 14 | 99 | Micro | 14980 | Micro | 3 | Micro | MICRO | 1 | Company 85 | 43974 | SME | 718455 | Large | 77 | SME | LARGE | 1 |
| Company 15 | 15937 | SME | 269859 | SME | 72 | SME | SME | 1 | Company 86 | 306903 | Large | 1000708 | Large | 40 | SME | LARGE | 1 |
| Company 16 | 2460 | SME | 54241 | SME | 22 | SME | SME | 1 | Company 87 | 1158 | Micro | 21440 | Micro | 3 | Micro | MICRO | 1 |
| Company 17 | 17115 | SME | 288713 | SME | 219 | Large | SME | 0.7375 | Company 88 | 51002 | SME | 830904 | Large | 10 | Micro | LARGE | 0.5 |
| Company 18 | 19025 | SME | 319280 | SME | 90 | SME | SME | 1 | Company 89 | 35045 | SME | 575595 | Large | 36 | SME | LARGE | 1 |
| Company 19 | 27375 | SME | 452871 | Large | 34 | SME | LARGE | 1 | Company 90 | 397326 | Large | 1271977 | Large | 31 | SME | LARGE | 1 |
| Company 20 | 12697 | SME | 218030 | SME | 231 | Large | SME | 0.8875 | Company 91 | 45511 | SME | 743051 | Large | 100 | SME | LARGE | 1 |
| Company 21 | 4461 | SME | 86254 | SME | 91.2 | SME | SME | 1 | Company 92 | 28611 | SME | 472653 | Large | 80 | SME | LARGE | 1 |
| Company 22 | 156279 | Large | 65820 | SME | 484 | Large | LARGE | 1 | Company 93 | 42997 | SME | 702820 | Large | 16 | SME | LARGE | 1 |
| Company 23 | 36606 | SME | 600564 | Large | 96 | SME | LARGE | 1 | Company 94 | 61111 | SME | 992653 | Large | 180 | SME | LARGE | 0.75 |
| Company 24 | 66321 | SME | 923638 | Large | 145 | SME | LARGE | 1 | Company 95 | 198430 | Large | 675290 | Large | 92 | SME | LARGE | 1 |
| Company 25 | 27856 | SME | 460575 | Large | 102 | SME | LARGE | 1 | Company 96 | 215324 | Large | 725973 | Large | 110 | SME | LARGE | 1 |
| Company 26 | 5289 | SME | 99497 | SME | 34 | SME | SME | 1 | Company 97 | 24882 | SME | 412986 | Large | 25 | SME | LARGE | 1 |
| Company 27 | 29444 | SME | 485986 | Large | 87 | SME | LARGE | 1 | Company 98 | 103181 | Large | 389544 | Large | 129 | SME | LARGE | 0.6646 |
| Company 28 | 35296 | SME | 579617 | Large | 43 | SME | LARGE | 1 | Company 99 | 29181 | SME | 481773 | Large | 50 | SME | LARGE | 1 |
| Company 29 | 32586 | SME | 536248 | Large | 0 | Micro | LARGE | 1 | Company 100 | 37243 | SME | 610763 | Large | 36 | SME | LARGE | 1 |
| Company 30 | 301776 | Large | 369852 | SME | 67 | SME | LARGE | 0.5409 | Company 101 | 3000000 | Large | 9080000 | Large | 56 | SME | LARGE | 1 |
| Company 31 | 42166 | SME | 689532 | Large | 60 | SME | LARGE | 1 | Company 102 | 46611 | SME | 760653 | Large | 34 | SME | LARGE | 1 |
| Company 32 | 111824 | Large | 148523 | SME | 250 | Large | LARGE | 1 | Company 103 | 3482 | SME | 577692 | Large | 12 | SME | LARGE | 1 |
| Company 33 | 196224 | Large | 159632 | SME | 81 | SME | LARGE | 1 | Company 104 | 3125 | SME | 64875 | SME | 9 | Micro | SME | 0.75 |
| Company 34 | 2883 | SME | 61008 | SME | 4 | Micro | SME | 1 | Company 105 | 24611 | SME | 408653 | Large | 26 | SME | LARGE | 0.963 |
| Company 35 | 4255 | SME | 82959 | SME | 5 | Micro | SME | 1 | Company 106 | 43226 | SME | 706490 | Large | 58 | SME | LARGE | 1 |
| Company 36 | 27633 | SME | 457007 | Large | 38 | SME | LARGE | 1 | Company 107 | 50000 | SME | 814875 | Large | 39 | SME | LARGE | 1 |
| Company 37 | 3161 | SME | 65457 | SME | 9 | Micro | SME | 0.75 | Company 108 | 3160 | SME | 65440 | SME | 8 | Micro | SME | 1 |
| Company 38 | 72226 | SME | 1018131 | Large | 23 | SME | LARGE | 1 | Company 109 | 44833 | SME | 732208 | Large | 56 | SME | LARGE | 1 |
| Company 39 | 61320 | SME | 995999 | Large | 117 | SME | LARGE | 1 | Company 110 | 5075 | SME | 96075 | SME | 7 | Micro | SME | 1 |
| Company 40 | 75333 | SME | 1067843 | Large | 63 | SME | LARGE | 1 | Company 111 | 4084 | SME | 80212 | SME | 6 | Micro | SME | 1 |
| Company 41 | 45775 | SME | 747281 | Large | 86 | SME | LARGE | 1 | Company 112 | 47887 | SME | 781067 | Large | 33 | SME | LARGE | 1 |
| Company 42 | 48445 | SME | 789994 | Large | 80 | SME | LARGE | 1 | Company 113 | 57111 | SME | 928653 | Large | 207 | Large | LARGE | 0.5875 |
| Company 43 | 3581 | SME | 72173 | SME | 2 | Micro | SME | 1 | Company 114 | 121470 | Large | 444411 | Large | 103 | SME | LARGE | 1 |
| Company 44 | 894257 | Large | 97854 | SME | 83 | SME | LARGE | 1 | Company 115 | 27525 | SME | 455268 | Large | 16 | SME | LARGE | 1 |
| Company 45 | 859 | Micro | 22524 | Micro | 3 | Micro | MICRO | 1 | Company 116 | 27411 | SME | 453453 | Large | 63 | SME | LARGE | 1 |
| Company 46 | 1044 | Micro | 22954 | Micro | 3 | Micro | MICRO | 1 | Company 117 | 27112 | SME | 448662 | Large | 31 | SME | LARGE | 1 |