Economics Bulletin

Volume 31, Issue 2

Evaluating a Self-Organizing Map for Clustering and Visualizing Optimum Currency Area Criteria

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Abstract

Optimum currency area (OCA) theory attempts to define the geographical region in which it would maximize economic efficiency to have a single currency. In this paper, the focus is on prospective and current members of the Economic and Monetary Union. For this task, a self-organizing neural network, the Self-organizing map (SOM), is combined with hierarchical clustering for a two-level approach to clustering and visualizing OCA criteria. The output of the SOM is a topologically preserved two-dimensional grid. The final models are evaluated based on both clustering tendencies and accuracy measures. Thereafter, the two-dimensional grid of the chosen model is used for visual assessment of the OCA criteria, while its clustering results are projected onto a geographic map.

I acknowledge the financial support from Jubileumsfonden vid Åbo Akademi and Dagmar och Ferdinand Jacobssons fond and Tomas Eklund for comments.
Citation: Peter Sarlin, (2011) "Evaluating a Self-Organizing Map for Clustering and Visualizing Optimum Currency Area Criteria", *Economics Bulletin*, Vol. 31 no.2 pp. 1483-1495.
Submitted: Nov 24 2010. **Published:** May 22, 2011.

1. Introduction

Optimum currency area (OCA) theory attempts to define the geographical region in which it would maximize economic efficiency to have a single currency. The seminal work on the OCA theory was done in the early 1900s by Abba Lerner (Scitovsky, 1984). However, the concrete OCA criteria suggested in the 1960s and 70s are the following: mobility of factors of production (Mundell, 1961), the degree of economic openness (McKinnon, 1963), product diversification (Kenen, 1969), the degree of financial integration (Ingram, 1969), similarity of inflation rates (Haberler, 1970 and Fleming, 1971) and the degree of policy integration (Tower and Willet, 1970).[1] For an overall review of the OCA theory, see Horvath (2003).

Research from the turn of last century concerns, however, mainly empirical assessments of the OCA theory. The empirical literature is divided into two groups of methods: econometric and pattern recognition techniques. Coenen and Wieland (2000), Smets and Wouters (2002), Banerjee et al. (2005) and Raguseo and Sebo (2008) explore OCA criteria using econometric techniques, while Eichengreen (1991), Bayoumi and Eichengreen (1992), Eichengreen and Bayoumi (1996), Alesina et al. (2002), Boreiko (2002), Komárek et al. (2003) and Kozluk (2005) employ pattern recognition techniques for assessing OCA criteria. The group of pattern recognition techniques consists also of a few studies that utilize computational clustering techniques for assessing prospective and current members of the Economic and Monetary Union (EMU). The clustering analyses have mainly employed fuzzy techniques, such as fuzzy c-means (FCM) clustering, and assume that Germany is the center country used for measuring convergence. By applying fuzzy clustering techniques to variables suggested by OCA theory, Artis and Zhang (2001; 2002) look for heterogeneities in the actual and prospective EMU membership. Similarly, Boreiko (2002) apply fuzzy clustering analysis on measuring the readiness of the accession countries of Central and Eastern Europe for the EMU. Boreiko's set of variables includes both the Maastricht criteria (nominal convergence) and the OCA criteria (real convergence). By a similar application of fuzzy clustering, Kozluk (2005) judges the suitability of the accession countries for the EMU in relation to current members using the OCA criteria, and measures readiness – and the effort it will take to fulfill the entry requirements – using the Maastricht criteria. Further, Ozer and Ozkan (2007, 2008a and 2008b) employed recently FCM clustering on identifying OCA variables that distinguish prospective and current EMU member countries. This paper is mainly based on the previous work done by Ozer and Ozkan.

Exploratory data analysis (EDA) attempts to describe different aspects of the phenomena of interest in an easily understandable form by illustrating the structures in a data set, but by simultaneously preserving information of the original data set. There exist two distinguishable categories of EDA methods: projection and clustering techniques. The clustering techniques, such as FCM clustering, attempt to reduce the amount of data by enabling analysis of a small number of clusters, whereas the projection methods, such as multidimensional scaling (MDS) and its many variants (Cox and Cox, 2001), attempt to project multidimensional data onto a lower dimension, while attempting to preserve the whole structure of the data set. When attempting analysis of multidimensional data, such as statistical OCA indicators, methods of EDA are feasible techniques. The clustering methods do not, however, enable visual representation of the data distribution, while the projection techniques do not enable simultaneous clustering.

The Self-organizing map (SOM) (Kohonen, 1982, 2001) is an unsupervised general purpose EDA tool that elegantly combines the goals of projection and clustering techniques,

[1] Additional studies in the early stage of the OCA theory are, for example, Corden (1972) and Ishiyama (1975). Subsequently, the OCA criteria have been reassessed in, for example, Bertola (1989), Giavazzi and Giovannini (1989), Artis (1991), Mélitz (1991), Krugman (1991), Krugman (1993) Tavlas (1993) and Tavlas (1994).

enabling utilization of the pattern recognition capabilities of our own human brains. On the one hand, the SOM projection differs from other projection techniques, such as MDS, by focusing on preserving the local neighborhood relations, instead of trying to preserve the global distances between data. Rather than projecting data into a continuous space, such as MDS methods, the SOM uses a grid of nodes onto which data are projected, and which are subsequently clustered. The two-level clustering of the SOM, i.e., separation of data into nodes and nodes into clusters as proposed by Vesanto and Alhoniemi (2000), differs from other statistical clustering techniques. In this paper, the second-level clustering is done using Ward's (1962) hierarchical clustering. Vesanto and Alhoniemi assert that the two-level clustering of the SOM differs from other clustering methods by being more robust on data that are non-normally distributed, by not needing *a priori* specification of the number of clusters, and by being efficient and fast especially in comparison with other clustering techniques. Thus, the mapping of the SOM may either be thought of as a projection maintaining the neighborhood relations in the data (Kaski, 1997) or as a spatially constrained form of *k*-means clustering (Ripley, 1996).

The applications of the SOM concern mainly studies in engineering and medicine (Oja et al., 2003), while it has been applied infrequently in macroeconomic time-series analysis. For example, Sarlin and Marghescu (2011) and Sarlin (2011) have used the SOM for monitoring indicators of currency and debt crises, respectively, while Länsiluoto et al. (2004) have used the SOM for analyzing the macro environment for the pulp and paper industry. The SOM has only been briefly introduced to analysis of economic convergence in Serrano-Cinca (1997). Our paper, however, differs by addressing specifically OCA convergence rather than convergence of the EU member states in general and in terms of countries, indicators, time span and visualization of the SOM output. We attempt to identify OCA variables that distinguish prospective and current EMU member countries. The created SOM model enables also analysis over time and across countries of convergence or divergence to the EMU on a two-dimensional plane. Further, we pair the SOM with a geospatial dimension by plotting the color code of the cluster representative, enabling a projection of multidimensional information on a geographic map. We also use an evaluation framework for choosing the model and introduce an OCA index for analysis of overall convergence. The visual explorations in this paper illustrate the usefulness of the SOM for clustering and visual monitoring of the OCA criteria. Since the projection preserves the neighborhood relations, not the absolute distances between data, the map will present convergence in a rank-ordered manner rather than showing absolute distances between countries.

The paper is organized as follows. The first part introduces the methodology used for assessing the OCA criteria. First, the SOM is introduced, whereafter the OCA criteria and sample of countries are discussed. The second part explains the training criteria and the construction of the SOM model. The third part shows visual analyses using the SOM model and a geospatial mapping. Finally, the fourth part concludes by presenting the key findings and recommendations for future research.

2. Methodology

2.1 Self-Organizing Maps

The SOM is a projection and vector quantization technique utilizing an unsupervised, competitive learning method developed by Kohonen (1982, 2001). Through projection, the SOM reduces the dimensions of the data space (as factor analysis does), while the vector quantization enables representation of data in specific mean profiles (as clustering does). Formally, the SOM performs a mapping from the input data space Ω onto a k-dimensional array of output nodes. In this paper, for visualization purposes k equals to 2. The vector quantization allows modeling from the continuous space Ω, with some probability density function $f(x)$, to a finite set of nodes. However, the location of these nodes on the map depends on the neighborhood structure of the data in the input space.

For its superior visual features, the software Viscovery SOMine 5.1 is used in this study.[2] It employs the batch training algorithm; instead of processing the data vectors sequentially, it processes all data vectors simultaneously. The training process starts with an initialization of the reference vectors. Instead of random initialization, the reference vectors are set in the same direction as the two principal components using principal component analysis (PCA). Following Kohonen (2001), this is done in three steps:

1. Determine the two eigenvectors, v_1 and v_2, with the largest eigenvalues from the covariance matrix of all data vectors x.
2. Let v_1 and v_2 span a two-dimensional linear subspace and fit a rectangular array along it, where the main dimensions are the eigenvectors and the center coincides with the mean of x. Thus, the direction of the long side is parallel to the longest eigenvector v_1 and its length is defined to be 80% of the length of v_1. The short side is parallel to v_2 and its length is 80% of the length of v_2.
3. Identify the initial value of the reference vectors $m_i(0)$ with the array points, where the corners of the rectangle are $\pm 0.4 v_1 \pm 0.4 v_2$.

This has been shown to lead to rapid convergence and enables reproducible models (Forte et al., 2002). The batch training algorithm operates according to the following two steps: (1) pairing the input data with the most similar nodes, or best-matching units (BMUs), and (2) adapting the BMU's, and its neighbors, reference vectors based on the paired data. The steps are repeated for a specified number of iterations.

In the first step, each input data vector x is compared with the network's reference vectors m_i,

$$\|x - m_c\| = \min_i \|x - m_i\|. \qquad (1)$$

such that the distance between the input data vector x and the winning reference vector m_c is less than or equal the distance between x and any other reference vector m_i. During the first step, all the input vectors are presented to the map.

In principle, the second step estimates the reference vectors m_i such that the distribution of the map fits the distribution of the input space. Formally, each reference vector m_i is adjusted using the equation for the batch algorithm:

$$m_i(t+1) = \frac{\sum_{j=1}^{N} h_{ic(j)}(t) x_j}{\sum_{j=1}^{N} h_{ic(j)}(t)}, \qquad (2)$$

where $h_{ic(j)}(t)$ is a weight that represents the value of the neighborhood function defined for the node i in the BMU $c(j)$ at time t. The index j indicates the input data vectors that belong to the node c, and N is the number of the data vectors. The function $h_{ic(j)} \in [0,1]$ is defined as a Gaussian function:

$$h_{ic(j)} = \exp\left(-\frac{\|r_c - r_i\|^2}{2\sigma^2(t)} \right), \qquad (3)$$

[2] For a thorough discussion of the software, see Deboeck (1998).

where r_c and r_i are two-dimensional coordinates of the reference vectors m_c and m_i, respectively, and the radius of the neighborhood $\sigma(t) \in (0,2]$ is a decreasing function of time *t*. Beginning from half the diagonal of the grid size ($\sigma = (X^2 + Y^2)^2 / 2$), the radius $\sigma(t)$ decreases monotonically towards a specified tension value. A rule of thumb is that a high tension results in stiff maps that stress topological ordering at the cost of quantization accuracy (Vesanto et al., 2003). The rest of the parameters in SOMine are the following: map size (the number of nodes), map format (the ratio of *X* and *Y* dimensions), and the training schedule (number of training cycles). Furthermore, the second-level clustering is done using a modified agglomerative hierarchical clustering. Starting with a clustering where each single node forms a cluster by itself, in each step of the algorithm the two clusters *k* and *l* with the minimal Ward (1962) distance are merged. The Ward distance is defined as follows:

$$d_{kl} = \begin{cases} \frac{n_k n_l}{n_k + n_l} \cdot \left\| c_k - c_l \right\|^2 & \text{if clusters } k \text{ and } l \text{ are adjacent} \\ \infty & \text{otherwise} \end{cases}, \tag{4}$$

where *k* and *l* represent two specific clusters, n_k and n_l the number of data points in the clusters and $\left\| c_k - c_l \right\|^2$ the squared Euclidean distance between the cluster centers of clusters S_k and S_l. For coherent clusters, the algorithm is modified to only merge clusters with neighboring clusters by defining the distance between non-adjacent clusters as infinitely large.

The quality of the map is measured in terms of quantization error (QE) and the distortion measure (DM) (Vesanto et al., 2003). The QE represents the fitting of the map to the data measured by an average of the distances between all input vectors x_i and their corresponding best matching reference vectors m_c, i.e.,

$$QE = \frac{1}{N} \sum_{j=1}^{N} \left\| x_j - m_{c(j)} \right\|^2 . \tag{5}$$

The normalized distortion measures the fit of the map with respect to both the shape of the data distribution and the radius of the neighborhood, and is computed as follows.

$$DM = \frac{1}{N} \frac{\sum_{j=1}^{N} \sum_{i=1}^{M} h_{ic(j)} \left\| x_j - m_i \right\|^2}{\sum_{j=1}^{N} \sum_{i=1}^{M} h_{ic(j)} \Big/ M} , \tag{6}$$

where *M* is the number of reference vectors, m_i is the *i*th reference vector, x_j is the *j*th data vector, and $h_{ic(j)}$ is the neighborhood function.

The output of the SOM algorithm is, for the purpose of this analysis, visualized using a mapping of the data points onto a two-dimensional plane. The dimensions of this plane are visualized using layers, namely feature planes. For each corresponding indicator, the feature planes represent graphically the distribution of the variable values on the two-dimensional map. In this paper, the feature planes are produced in color, where low to high values are represented by cold to warm scales. The color scales are shown below each corresponding feature plane. For visual interpretation purposes, the distances between each node and its corresponding cluster center are shown by shading the clusters; nodes close to the center take a lighter color and nodes further away take a darker color.

2.2 Choice of Countries, Indicators and Index

The utilized data set is a replica of the data used in Ozer and Ozkan (2007). The computation of the OCA variables and the choice of countries follows the practice in Artis and Zhang (2001 and 2002), Boreiko (2003), Kozluk (2005). The set of countries is representative for current and prospective EMU member countries.[3] Further, two benchmarks (Canada and Japan) are included to also account for a control group. A representative set of countries enables exploration of possibly divergent countries. Although enabling analysis of EMU member countries is the main target of this paper, it is important to include the other states of OCA criteria to enable temporal analysis between various states. The data set used in this study includes cross-sectional data for 26 countries. Although temporal data have not been collected for this paper, the projection of the OCA criteria over time would be a meaningful further refinement for assessing convergence or divergence of countries over time.

The indicators and their descriptive statistics are shown in Table 1, while sources, frequency and time interval of the data can be found in the Appendix. *Synchronization in business cycles* is represented by the cross-correlation of the cyclical components of deseasonalized industrial production series with that in Germany. Following Artis and Zhang (2001 and 2002) and Boreiko (2003), the detrending is done using the Hodrick-Prescott (H-P) filter (Hodrick and Prescott, 1997) with a smoothing parameter of 50,000. *Synchronisation in the real interest rates* is represented by the cross-correlation of the cyclical components of the real interest-rate cycle of a country with that in Germany. The real interest rates have been obtained by deflating with consumer price indices and detrended utilizing the H-P filter with optimum smoothing parameters based on the nature of the time-series data (Dermoune et al., 2006: 2-4) as also done in Schlicht (2005). For both cross-correlation variables, -1 represents perfect negative correlation (perfect desynchronization) and 1 perfect positive correlation (perfect synchronization). *Volatility in the real exchange rates* is represented before 1999 by the standard deviation of the log-difference of bilateral real exchange rates with the Deutsche Mark and after 1999 with that of the Euro. To obtain real exchange rates, nominal rates have been deflated by relative wholesale and producer price indices, as available. For Portugal, the consumer price index is used instead. *Degree of trade integration* is measured by $\left(x_i^{EU25} + m_i^{EU25}\right) / \left(x_i + m_i\right)$ where x_i and m_i represent total exports and imports of country *i* and x_i^{EU25} and m_i^{EU25} represent exports and imports of country *i* to and from European Union countries *EU25* as of May 2004 (Jules-Armand, 2007). *Convergence of inflation* is measured by $e_i - e_g$, where e_i and e_g represent the respective inflation rates in country *i* and Germany. The reason for collapsing the panel data to a cross section is that for the variables measuring inflation and trade we have only collected data for one year. In the future, the main task will be to collect an extensive panel data set for up-to-date temporal analysis.

Table 1. Descriptive statistics of the OCA criteria.

VARIABLES	*OBS*	*MEAN*	*STD.DEV*	*MIN*	*MAX*
Synchronization in Business Cycles	26	0.46	0.27	-0.11	0.90
Synchronization in the Real Interest Rates	26	0.33	0.41	-0.60	0.95
Volatility in the Real Exchange Rates	26	0.01	0.01	0.00	0.07
The Degree of Trade Integration	26	64.91	17.90	8.38	83.13
Convergence of Inflation	26	0.73	1.96	-2.23	7.04
OCA Index	26	0.71	0.14	0.38	0.93

The above criteria are used for computing an OCA index. For a consistent index, the criteria have been transformed and normalized as follows. First, volatility in the real exchange rate is multiplied by -1, so that an increase in the criterion indicates convergence to the currency area. Since both positive and negative inflation differentials indicate divergence,

[3] The countries are Austria, Belgium, Croatia, Cyprus, Czech Republic, Denmark, Finland, France, Greece, Hungary, Ireland, Italy, Luxembourg, Netherlands, Norway, Poland, Portugal, Romania, Slovak Republic, Slovenia, Spain, Sweden, Turkey and United Kingdom.

we define it as the negative deviation from zero measured by $-\left\| e_i - e_g \right\|$, as above. For standardizing the contribution of each criterion, they are normalized columnwise by range. Finally, the index is defined as the country-specific average of the normalized criteria.

3. The SOM Model

3.1 Training Criteria

Ozer and Ozkan (2008b) show that the first three principal components explain more than 80 % of the variability in the data. Thus, by exploring the three principal components, the general structure of the data can be quite accurately assessed. In particular, both Canada and Japan, and Turkey and Romania form their own clusters, while the rest of the countries are grouped in a sparse cluster, indicating differences across these countries. Following Ozer and Ozkan (2008b), the performance of the SOM analysis can be assessed using the following clustering tendencies in the data:

1. Canada and Japan form their own cluster
2. Turkey and Romania form their own cluster
3. At least 12 EMU members form their own cluster

Further, for assessing states that differ from the countries that have converged to the EMU, a further criterion is the existence of two additional clusters, each with at least two countries, be they EMU members, accession countries or benchmarks. Thereby, since EMU members may be mapped into the differing states, it is appropriate to only require 11 EMU members for criterion 3. In addition to the above criteria, the maps are further assessed based on two accuracy measures on the fit of the map to the data distribution, the QE and the DM, and based on interpretability, measured by the visual cluster structure. For the set of experiments, the maps with QE and DM in the 50th percentile are evaluated as accurate. Percentiles are preferred over absolute thresholds on the measures, since the absolute values of the QE and DM are not informative; they are dependent on the used data sample and should be compared with models on the same sample. The topographic ordering of the maps is evaluated using Sammon's mapping (1969), a non-linear mapping from a high-dimensional input space to a two-dimensional plane. We use it for assessing the topological relations of the reference vectors on 3D planes. Topographic ordering is defined to be adequate if the map is not twisted at any point and has only adjacent nodes as neighbors in the data space. To sum up, most of the criteria concern the clustering tendency, while only the topological ordering assesses the visual quality. The distribution of the criteria is motivated by mainly aiming at proper clustering of the OCA criteria, but on the side also preferring an easily interpretable, intuitive map.

3.2 Training the SOM Model

For equal weighting of the indicators and a computation-wise easier training process, the OCA criteria have been standardized by variance. The constructed map is trained using 26 row vectors – one for each country – with a dimensionality of 5 – one for each variable. The OCA index is not included in finding each BMU (Eq. 1), it is only associated to the map using Eq. 2. During the course of the experiment, several maps were trained using different parameter values (tension, cycles of training, number of clusters, number of nodes and map format). In the final experimental stage, the map format is, however, kept constant. The map format is chosen to be 75:100, since Kohonen (2001, p. 120) recommend that the map ought to be of oblongated form, rather than square, in order to achieve a stable orientation in the data space. The number of clusters is, according to the training criteria on the clustering tendencies, chosen to be five; one for Canada and Japan, one for Romania and Turkey, one for the EMU members and two for assessing differing states. The parameters that have been varied are tension and number of nodes.

Table 2. The SOM experiments.

Tension	0,0001							0.3							0.5							0.75							1							1.5							2						
Neurons	1	2	3	4	5	6	7	1	2	3	4	5	6	7	1	2	3	4	5	6	7	1	2	3	4	5	6	7	1	2	3	4	5	6	7	1	2	3	4	5	6	7	1	2	3	4	5	6	7
9	x	x		x			x	x	x		x			x	x			x			x				x			x				x			x				x			x				x			x
22-27	x	x	x	x		x		x	x		x	x	x		x	x		x			x	x	x		x			x	x	x		x			x	x			x			x				x			x
45-52	x	x	x	x	x	x		x	x	x	x	x	x		x	x	x	x	x	x		x	x		x			x	x	x		x			x	x	x		x			x				x			x
76-85	x	x	x	x	x	x		x	x	x	x	x	x		x	x	x	x	x	x		x	x	x	x	x	x		x	x		x			x	x	x		x			x	x	x		x			x
115-137	x	x	x	x	x	x		x	x	x	x	x	x		x	x	x	x	x	x		x	x	x	x	x	x		**X**	**X**	**X**	**X**	**X**	**X**	**X**	x	x		x			x	x	x		x			x
137-188	x	x	x	x	x	x		x	x	x	x	x	x		x	x	x	x	x	x		x	x	x	x	x	x		x	x	x	x	x	x		x	x		x	x		x	x	x		x			x
188-247	x	x	x	x	x	x		x	x	x	x	x	x		x	x	x	x	x	x		x	x	x	x	x	x		x	x	x	x	x	x		x	x		x	x	x	x	x	x		x			x

Note: The chosen map is shown in bold and X marks in columns 1–7 indicate quality measure fulfillment. The columns per tension value represent the following quality measures: 1, Canada and Japan form their own cluster; 2, Turkey and Romania form their own cluster; 3, at least 11 EMU members form their own cluster; 4, existence of two additional clusters with at least two countries each; 5, QE is in the 50th percentile; 6, DM is in the 50th percentile; 7, adequate topographic ordering.

Although Kohonen (2001, p. 111) notes that the selection of the parameters is not crucial if the map size is less than a few hundred nodes, the experiments show that different parameter values still result in varying outcomes. The SOM experiments are shown in Table 2 and resulted in the following conclusions. The experiments show that increasing the tension value leads to imprecise clustering, measured both by the clustering tendencies and the accuracies, while it leads to a better topographic ordering of the map. Increases in the number of nodes leads, on the other hand, not only to precise clustering, but also to a decrease in the topographic ordering. Based on the seven training criteria, the best SOM model is chosen. In Table 2, it is shown that the accuracy and ordering of the maps meet in the middle of the table, i.e., combining the accuracy and the ordering of the map.

After the extensive training process, a neural network with 5 nodes in the input layer and 137 output nodes ordered on a map of the size 13 x 10 was chosen. The data were trained with a tension of 1 (where $\sigma(t) \in [0,2]$) for 7 cycles, resulting in a QE of 0.09 and a DM of 0.79. The two-dimensional topological grid is shown on the left in Figure 1, while its feature planes are shown on the right. Data are subsequently projected onto the map using Eq. (1).

4. The SOM for Mapping Countries Based on the OCA Criteria

The clusters, and the subsequently projected data, in Figure 1 can be assessed using the feature planes in Figure 2. The feature plane for the OCA index (Figure 2) shows a composite measure of convergence for each country. The map in Figure 1 shows that the most dissimilar countries, i.e., Canada and Japan, and Romania and Turkey, are mapped into Cluster 1 and 2 in the upper corners of the map. Cluster 1 (C1) is especially characterized by high volatility in the real exchange rate and a positively diverging inflation rate, while Cluster 2 (C2) shows low values of the degree of trade integration and a strong negative divergence of the inflation rate. For both clusters, the rest of the criteria show medium values. Interestingly, Japan and Canada (C2) are shown to have higher convergence than Romania and Turkey (C1). Cluster 3 (C3) and Cluster 4 (C4) represent states that slightly differ from convergence with EMU. C3 shows a low synchronization in business cycles and real interest rates and a high degree of trade integration, while otherwise representing neutral values. C4 is, especially, characterize by a high synchronization in business cycles and a low in real interest rates. In C3, only the Slovak Republic out of three countries is a member country, while in C4, only Greece and Slovenia out of four countries are members of the EMU. Finally, Cluster 5 (C5) represents convergence with the EMU. It is characterized by high synchronization in business cycles and real interest rates, degree of trade integration and convergence of inflation, and low volatility in the real exchange rate. Eleven out of the 15 countries in C5 are EMU members.

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The non-EMU countries that show convergence are Denmark, Norway, Poland and Sweden, i.e., three Nordic countries.

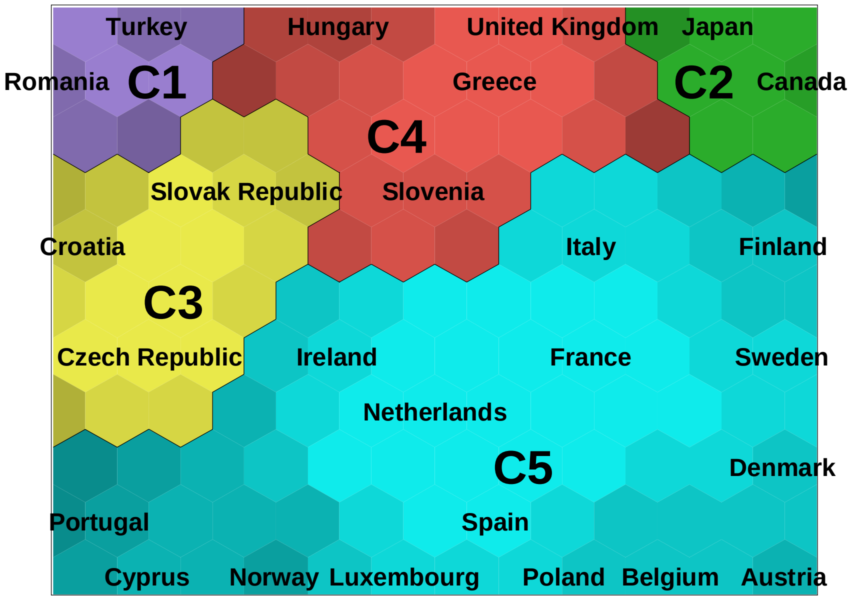

Figure 1. The two dimensional SOM grid.

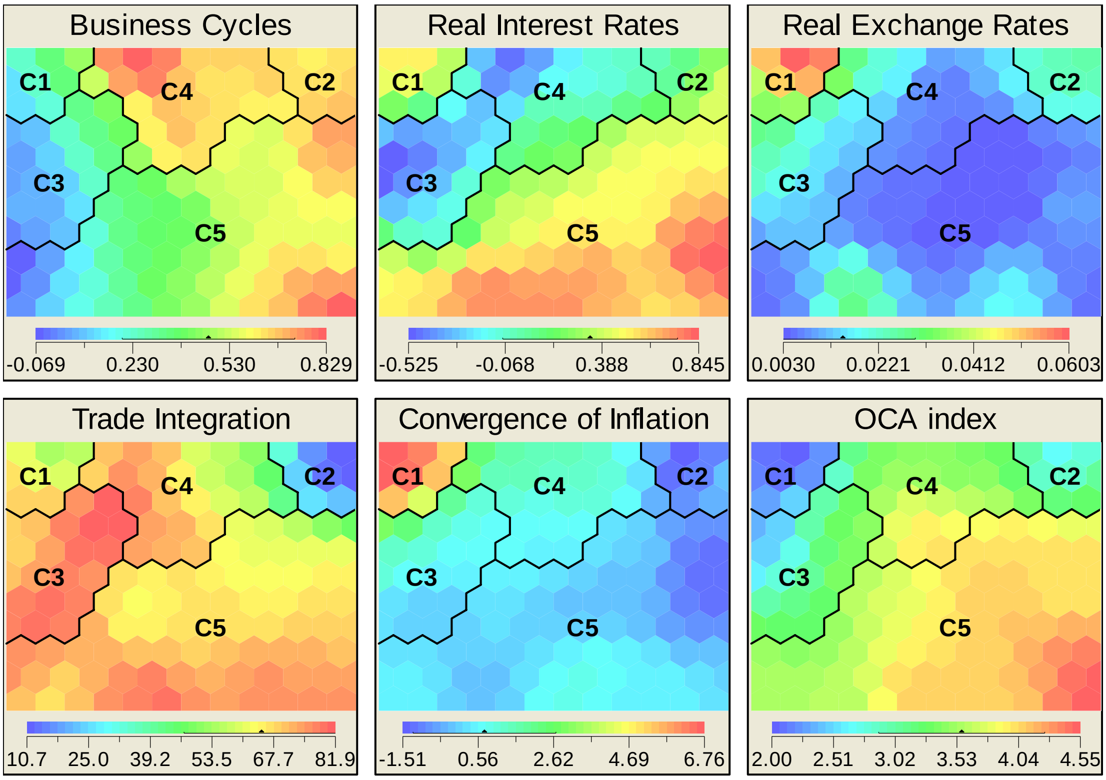

Figure 2. The feature planes of the SOM grid.

4.1 A Geographic Representation of the SOM Clusters

For further visual representation, the clustering results can be projected on a geographic map. By projecting the color code of each cluster on a geographic map, we can combine the multidimensional data dimensions with a geospatial dimension. We restrict the geographic area of interest to Europe, since visualizing the clustering results of the two correctly clustered benchmark countries does not bring any real added value. Germany is included into the EMU cluster (C5), since it is converged by definition of the criteria. The mapping onto a geographic map is shown in Figure 3. The geospatial dimension shows that the countries, be they EMU or non-EMU countries, mapped into the differing states of the EMU are mainly in Eastern Europe, while the United Kingdom is the only Western European country mapped into any of Clusters 1–4. In Figure 3, the economic region with the highest convergence is shown in light blue (Cluster 5).

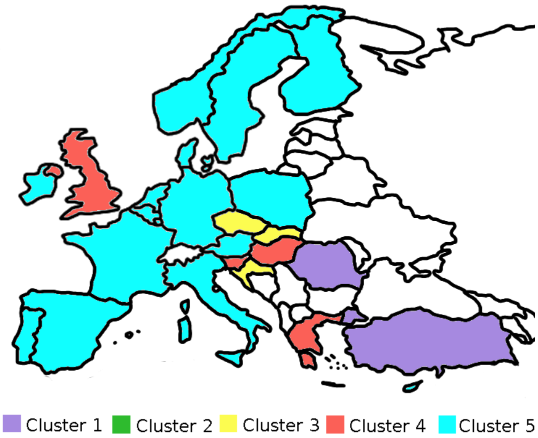

Figure 3. A projection of the clustering results on a geographic map (excluding benchmarks).

5. Conclusions

In this study, we have identified, clustered and visualized OCA criteria that distinguish prospective and current EMU member countries. Further, this study pairs the SOM with a geospatial dimension by plotting the color coding of the cluster representative, enabling a projection of multidimensional information on a geographic map. The visual explorations in this paper illustrate the usefulness of the SOM for clustering and visual monitoring of the OCA criteria. The novelty of this two-level clustering approach is a simultaneous visualization of the clustering results, and the inclusion of the geospatial dimension. Future work includes performing the framework presented in this paper on an extended panel data set for up-to-date analysis, especially for assessing convergence over time.

Appendix 1

Table A. Sources, frequencies and time intervals of the data (as per Ozer and Ozkan, 2007).

Variables	Frequency	Data Sources	Time Interval
Real exchange rates	monthly	IFS, TURKSTAT	1996:1-2005:6
Industrial production series	monthly	IFS	1991:1 - 2006:12
Real interest rates	monthly	IFS, EUROSTAT, Central Bank of Luxembourg	1997:2-2006:10
Trade data	annual	UNCTAD, Handbook of Statistics Online	2004
Inflation data	annual	WDI	2005

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