DOES ROOF SHAPE MATTER? SOLAR PV INTEGRATION ON ROOFS

N. Mohajeri[1]*, D. Assouline[1], B. Guiboud[1], J.L. Scartezzini[1]

[1]Solar Energy and Building Physics Laboratory (LESO-PB), Ecole Polytechnique Fédérale de Lausanne (EPFL), 1015 Lausanne, Switzerland

*Corresponding author; e-mail: mohajeri.nahid@epfl.ch

Abstract

This paper focuses on roof-shape classifications and solar potential for integrating photovoltaics (PV) on roofs. A machine-learning approach, Support Vector Machine (SVM), is used to classify the roof shapes in the city of Geneva. The impact of various roof characteristics on the solar potential is assessed and analysed. Monthly solar irradiation on rooftops, freely accessible from www.ge.ch/sitg using GIS LiDAR data (resolution 50cm by 50cm), is used in the analysis. The SVM identifies 6 types of roof shapes correctly in 66% of cases, that is, flat, gable, hip, gambrel & mansard, cross/corner gable & hip, and complex roof. We rank the roofs based on the complexity of their shape, useful area for PV, and potential for receiving solar energy. The results show that for most roof shapes the ratio between useful roof areas and the building footprint area is close to one, the main exception being gable where the ratio is 1.18, suggesting that the footprint is a good measure of useful PV roof area. The flat roof has the second highest useful roof area for PV (the complex roof being the highest) and the highest PV potential (in GWh). By contrast, hip roof has the lowest PV potential. Solar roof-shape classification provides basic information for designing new buildings, retrofitting interventions on the building roofs and efficient solar integration on rooftops. The results for the city of Geneva suggest that a data-driven approach is very useful for roof-shape classifications which can be expanded to national scale.

Keywords:

Machine learning; Roof-shape classification; Solar potential; Support Vector Machine

1 INTRODUCTION

There have been several studies focusing on the modelling of rooftop solar potential at neighbourhood and urban scale using different methods. For example, Wiginton et al. [1] use the sampling technique as well as the GIS-based Feature Analyst (FA) tool to estimate the rooftop PV potential. Nowak et al. [2] use statistical methods to estimate the solar PV potential for building roofs and facades at the national scale. Several other studies use aerial images and ArcGIS LiDAR data to determine roof geometries and to estimate the PV potential at a large scale [3, 4, 5, 6, 7, 8]. By contrast, Assouline et al. [9] use a machine learning approach to estimate the building rooftop solar PV potential for Switzerland. Other recent studies on modelling roof geometries for solar applications based on a simplification of roofs include the following [10, 11]. However, the classification of roof shapes (e.g. flat, gable, shed, hip), that is, roof architecture in relation to their solar potential has, so far, received little attention. In this paper, we focus on the city of Geneva as a case study, due to the availability of high resolution GIS data for roof geometries. The city of Geneva is composed of 16 neighbourhoods with a total of about 11,400 buildings (Fig. 1). The total area of the city is about 16 km^2 with a population density of 12,000 per km^2. About 92% of the total land in the city is used for built-up area, of which about 50% are buildings.

The main aim of this paper is to apply a data-driven methodology for classifying different roof shapes in relation to their potential for receiving solar energy.

G. Habert, A. Schlueter (eds.): Expanding Boundaries © 2016 vdf Hochschulverlag AG an der ETH Zürich
DOI 10.3218/3774-6_21, ISBN 978-3-7281-3774-6, http://vdf.ch/expanding-boundaries.html

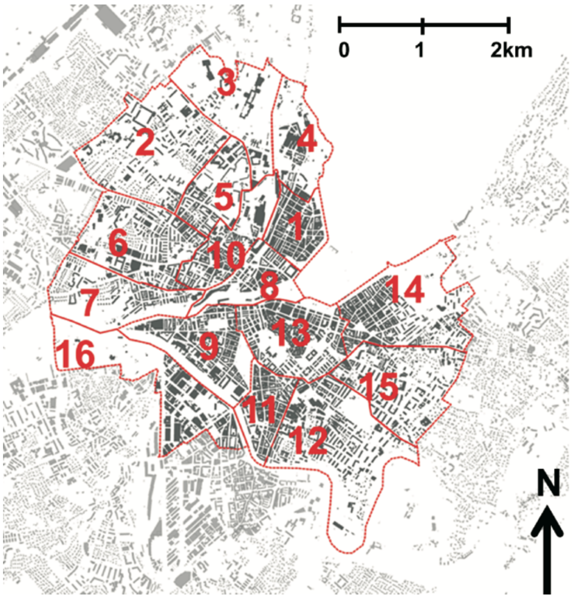

Fig. 1: Building map of the city of Geneva, composed of 16 neighbourhoods, each one marked by red broken line.

2 METHODOLOGY

To classify the building roofs in the Geneva city according to their shapes, GIS and Machine Learning algorithms have been used. Support Vector Machines (SVM) is one of the most efficient machine learning algorithms for classification tasks. It was initially developed by Cortes and Vapnik in 1995 [12]. The following section gives a short description of the main principles of the algorithm. This is followed by a section on the application of the method for classifying the roof shapes in the city of Geneva.

2.1 Support Vector Machine (SVM) Model

The Support Vector Machines (SVMs) are primarily an example of a linear classifier [12, 13, 14]. They can, however, be extended to non-linear classifier with kernel functions. SVM is a machine learning technique based on the concept of decision planes (hyperplanes) which define the decision boundary of the classifier. A classifier separates a set of objects into their respective classes with a line. A hyperplane is optimal if it maximizes the margin of separation between the two classes. Some objects may not be linearly separable. For these, a non-linear classifier is defined. To move from a linear classifier to a non-linear classifier, a set of mathematical functions known as kernels is defined. The performance of SVM depends heavily on the choice of the kernel function, $K(x_i, x_j)$. There are number of kernels that can be used in Support Vector Machines models. These include linear, polynomial, radial basis function (RBF), and sigmoid. The RBF is by far the most popular choice of kernel types used in Support Vector Machines. The following is the Gaussian radial basis function:

$$K(x_i, x_j) = \exp\left(-\gamma |x_i - x_j|^2\right) \qquad (1)$$

where γ > 0 is a parameter that controls the width of Gaussian kernel function. It plays a similar role as the degree of the polynomial kernel in controlling the flexibility of the resulting classifier. Using the kernel function, we implicitly map the input data to a so-called feature space, where the function can be modelled as a linear function. We compute the following Eq. (2):

$$K(x_i, x_j) = \langle \phi(x_i), \phi(x_j) \rangle \qquad (2)$$

where $K(x_i, x_j)$ is the kernel function and ϕ is mapping from the original input space to the feature space. As mentioned, Support Vector Machine (SVM) is primarily a classification method that separates objects of different classes by constructing hyperplanes in a multidimensional space. To construct an optimal hyperplane, SVM employs an iterative training algorithm, which is used to minimize a function. Depending on the error function, SVM models can be used for classification or regression. Minimizing the error function while training the data, leads to the following constrained optimization problem [12, 13, 14]:

$$\text{Minimize} \quad \frac{1}{2}\|w\|^2 + C\sum_{i=1}^{N} \xi_i \quad C > 0 \qquad (3)$$

Subject to:

$$y_i\left(\langle w, x_i \rangle + b\right) \geq 1 - \xi_i \text{ and } \xi_i \geq 0, i = 1, \ldots, N$$

where *C* is the capacity constant, a tuning parameter, which controls errors and thus controls the generalization ability of an SVM. w is the weight vector, that is, an unknown vector to be optimised, *b* is a constant, and ξ_i is slack variable so as to deal with the outliers. x_i is the training vector*,* so the index *i* labels the *N* training samples that are mapped into a higher dimensional space by the function ϕ. It should be noted that the larger the *C*, the more the error is penalized. Thus, *C* should be chosen with care to avoid over fitting. By choosing a low C, the risk of overfitting an SVM on the training sample is reduced. Before applying the methodology for roof-shape classification, several roof-shape characteristics have been analysed in the next section.

G. Habert, A. Schlueter (eds.): Expanding Boundaries © 2016 vdf Hochschulverlag AG an der ETH Zürich
DOI 10.3218/3774-6_21, ISBN 978-3-7281-3774-6, http://vdf.ch/expanding-boundaries.html

3 ANALYSING ROOF CHARACTERISTICS

We analyse the roof characteristics including roof orientation, roof aspect, and roof slope for the all the buildings in the city of Geneva (Figs. 2, 3). Yearly and monthly solar irradiation for roofs has been estimated using GIS LiDAR data (www.ge.ch/sitg/) and is freely accessible. Fig. 2a shows the distribution of roof tilted-angles.

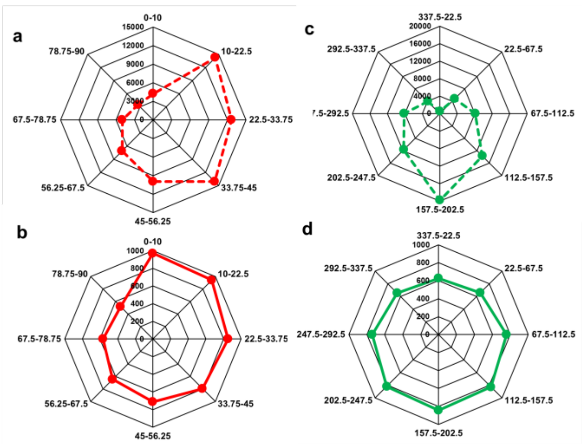

Fig. 2: Frequency distribution of different roof slopes and roof aspects (a, c). Yearly mean solar irradiation, kWh/m^2, for different aspect and slope ranges (b, c).

The highest frequency belongs to roofs with the slope between 10 degrees and 45 degrees. The lowest frequency belongs to buildings with a 0 to 10 degrees slope (flat roofs). Regarding the roof aspects (the direction in which a roof faces), those roofs that are facing to the south-east, south, and south-west have the highest frequency (Fig. 2c). We use the estimated yearly solar irradiation for rooftops (www.ge.ch/sitg/) in order to analyse the solar potentials in relation to slope range and aspect range. Figs. 2b shows that while the flat roofs (0-10 degrees slope) have the lowest frequency they receive the highest solar irradiation. The second highest solar irradiation belongs to roofs with slopes between 10 to 45 degrees. Fig. 2d shows that roofs facing to south-east, south, and south–west receive the highest solar irradiation. Whereas roofs facing to the north, north-east, and north-west receive comparatively little solar irradiation. The roof orientation is thus a very important roof characteristic (Fig. 3).

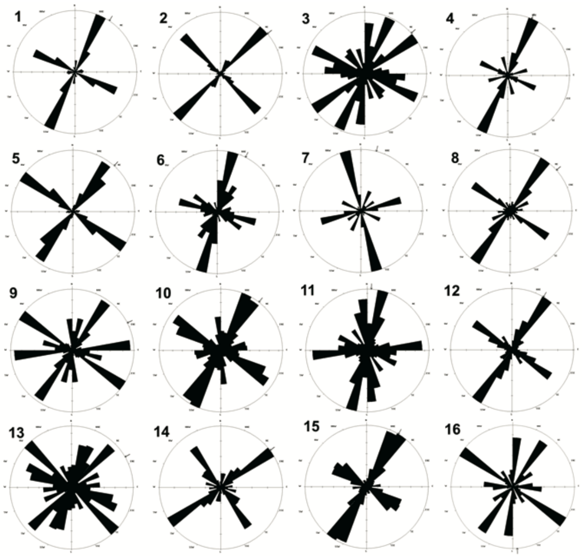

Fig. 3 Frequency distribution of roof orientations for the 16 neighbourhoods shown in Fig. 1

We use circular statistics visualized by rose diagrams to show the orientation of roofs in the city of Geneva. To understand better the distribution of roof orientations, we divide the city into 16 neighbourhoods and for each neighbourhood the roof orientations have been plotted using a rose diagram (Fig. 3). The rose diagrams show that for most of the neighbourhoods roofs trending south-west and north-east have the highest frequency (number 1, 2, 4, 6, 8, 10, 11, 12, 14, 15). For several neighbourhoods (3, 9, 13, 16) the rose diagrams show a circular distribution indicating that roofs trending in all directions.

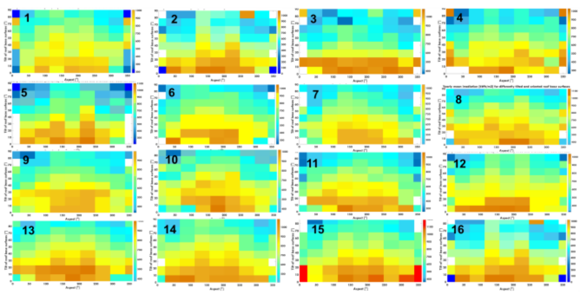

Fig. 4. Yearly mean solar irradiation [kWh/m2 year] as a function of the slope [0-90°] (y-axis) and aspect [0-360°] (x-axis) of the roof surfaces for the 16 neighbourhoods.

G. Habert, A. Schlueter (eds.): Expanding Boundaries © 2016 vdf Hochschulverlag AG an der ETH Zürich
DOI 10.3218/3774-6_21, ISBN 978-3-7281-3774-6, http://vdf.ch/expanding-boundaries.html

For each neighbourhood we use MATLAB in order to create 3D plot of solar irradiation, roof aspect, and roof slope (Fig. 4). For all the neighbourhoods, we find that the yearly mean solar irradiation (kWh/m^2) varies depending on roof slopes and roof aspects. However, the highest solar irradiation belongs to roof slopes between 0 - 30 degrees and roof aspects between south-east and south-west. Combining all the neighbourhoods, we plot yearly mean solar irradiation [kWh/m^2], for all the roof surfaces in the city of Geneva, as a function of roof slope and roof aspect (Fig. 5). The results are consistent with the neighbourhood results and show that the highest solar irradiation belongs to slopes 0-30° and roof aspects 112.5°-247.5°.

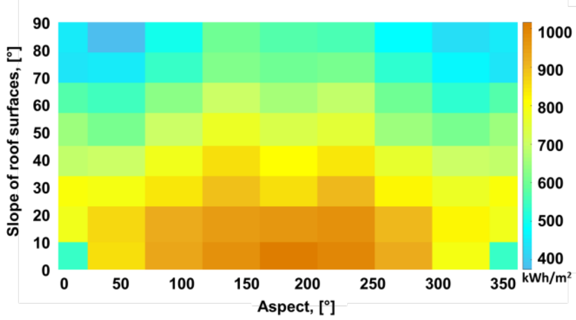

Fig. 5: Yearly mean solar irradiation [kWh/m2 year] as a function of the slope [0-90°] (y-axis) and aspect [0-360°] (x-axis) of the roof surfaces for the city of Geneva.

4 SUPPORT VECTOR MACHINE (SVM) FOR ROOF CLASSIFICATION

The total number of buildings chosen and classified for this study of the city of Geneva is 11,400. The most common roof shapes of buildings in Geneva are flat, shed, gabled, hipped, gambrel, mansard flat, mansard hipped, cross-hipped, cross-gabled, corner-hipped, corner-gabled, pyramidal, and complex (mixed of several mentioned roof shapes). Some of these roof shapes, however, are difficult to classify properly and use. For the present purpose the above roof shapes have been divided into 6 main groups, namely flat, gabled, hipped, gambrel and mansard, cross/corner hipped and gabled, and complex. In order to apply SVM for classification of roof shapes, the following steps are taken:

(i) Feature selection. The following features that characterize the roof shapes have been selected:

- Frequency distribution of roof surface aspects (bin width 22.5°, from 0 to 360°)
- Frequency distribution of roof surface slope (bin width 10°, from 0 to 90°)
- Number of surfaces for different roof shapes
- Percentage of surface area within a certain slope range (bin width) to total surface area
- Percentage of surface area within a certain aspect range (bin width) to total surface area

(ii) Scale the entire data. In this step, each feature is normalized by subtracting the mean of the feature and dividing it by the standard deviation. The label data also needs to be scaled.

(iii) Label data. The label data is used to train and test the classifier using SVM so as to apply the classifier for the rest of the data. No labelled data exists for Geneva roof shapes; thus, we need to label the data manually. 717 buildings (about 6% of total data) were manually labelled using a high quality aerial map from Swisstopo (https://map.geo.admin.ch) as well as Google Earth. We also label a similar quantity of buildings for each type of roofs (flat: 127, gabled: 127, hipped: 124, gambrel and mansard: 118, cross and corner hipped and gabled: 115, complex roofs: 106). SVM is use to classify the roof shapes for the rest of the buildings (11089).

(iv) Testing and training in SVM.

- The labelled data is divided into two unequal parts: 75% for training and cross validation and 25% for testing the classifier.
- Radial basis function kernel is chosen because it offers the best accuracy.
- Cross-validation is a model validation technique for assessing how the training dataset can be generalized to an independent dataset. K-fold cross-validation (the original sample is randomly partitioned into *k* equal-sized subsamples) is used in this study. K equal to 6 is set as the best for our data.
- SVM classifier from the above step is used on the rest of the data to predict the roof shapes of the rest of the buildings in the city of Geneva.
- Finally, classification accuracy metric is used to evaluate the performance of classifier. The metric is defined as:

$$accuracy = \frac{\psi}{\Omega} * 100\%$$

Where ψ is the number of correctly classified samples and Ω is the total number of samples.

5 RESULTS

The SVM classifier is able to identify the 6 types of roof shapes correctly in 66% of cases, that is, flat, gable, hip, gambrel & mansard, cross/corner gable & hip, and complex roofs. The results (Fig. 6) show that flat roofs, after complex roofs, have the second highest useful roof area for PV (normalized by the number of buildings in each category). The cross/corner gable & hip and gambrel and mansard are ranked as third and fourth, respectively. Hip and gable have the lowest useful area for PV production.

G. Habert, A. Schlueter (eds.): Expanding Boundaries © 2016 vdf Hochschulverlag AG an der ETH Zürich
DOI 10.3218/3774-6_21, ISBN 978-3-7281-3774-6, http://vdf.ch/expanding-boundaries.html

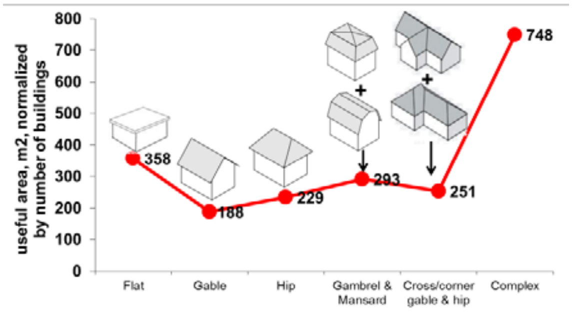

Fig. 6: Normalized useful roof areas for PV for different types of roof shapes.

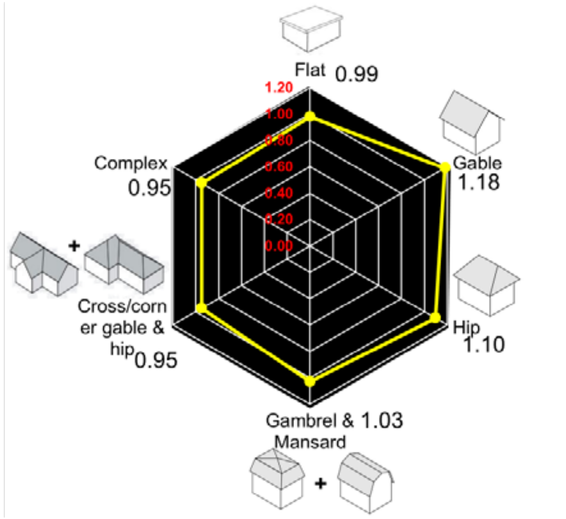

Fig. 7: Ratio of useful roof area to footprint area for different roof shapes.

The complex roofs belong to buildings with complex shape and large surface roof area such as museums, stations, and cathedrals and thus have much higher useful roof area than cross/corner gable & hip roofs.

The available roof area is estimated after removing the superstructures from the roofs, as well as 1m^2 from the margin of roof surfaces, and considering the 28m^2 threshold (only areas larger than 28m^2 are considered) for roofs due to the size of PV panel. Given the availably of the building footprint areas, it is also very useful to estimate the ratio of useful roof area for each type of roof shape to building footprint area (Fig. 7). For most of the roof shapes the ratio is close to one indicating that the footprint area can be used as a measure of the area available for PV. However, for hip and gable roofs the ratios are 1.10 and 1.18 (due to their steep slopes), respectively, making the footprints, particularly for the gable, less accurate estimates for PV areas.

For each roof shape, the yearly mean solar irradiation (kwh/m^2) and the PV potential (kWh) are calculated (Fig. 8). The results show that flat roofs have the highest yearly mean solar irradiation, followed by the cross/corner hip & gable roofs and the hip roofs. Gable roofs receive the least solar irradiation. The PV potential for roof shape in Geneva shows that flat roof and complex roof are the highest and gable is the lowest.

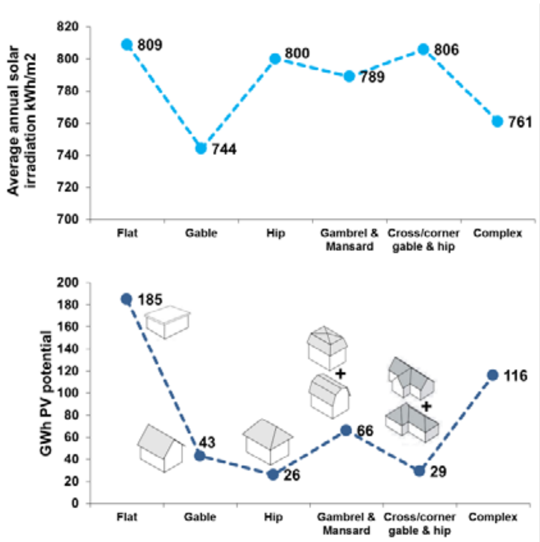

Fig. 8: Upper diagram, yearly mean solar irradiation (kwh/m2); lower diagram, PV potential (GWh) for different roof shapes.

6 SUMMARY

In this paper we use a data-driven approach to classify the roof shapes, the available roof areas for PV installation, and their potential for solar energy. The solar roof-shape classification provides basic information for designing new buildings, retrofiring innervations on the building roofs, as well as efficient solar integration on rooftops.

7 ACKNOWLEDGMENTS

This research has been financially supported by CTI (Commission for Technology and Innovation) within SCCER FEEB&D (CTI.2014.0119).

8 REFERENCES

1. L. Wiginton, H. Nguyen, and J. Pearce. Quantifying rooftop solar photovoltaic potential for regional renewable energy policy. Computers, Environment and Urban Systems, 34(4): 345–357, 2010.

2. S. Nowak, M. Gutschner, D. Ruoss, P. Togweiler, T. Schoen. Potential of building integrated photovoltaics. Report IEA-PVPS T7-4; 2002.

3. J. Goodling, R. Crook, A.S. Tomlin. 2015. Modelling of roof geometries from low-resolution LiDAR data for city-scale solar energy applications using a neighbouring buildings method. Applied Energy 148 (2015) 93–104.

4. Tarsha-Kurdi F, Landes T, Grussenmeyer P, Koehl M. Model-driven and data-driven approaches using LIDAR data: analysis and comparison, Munich 2007. p. 87–92.

5. M.C. Brito, N. Gomes, T. Santos, J.A. Tenedorio. Photovoltaic potential in a Lisbon suburb using LiDAR data. Solar Energy 86 (2012) 283–288.

6. C. Carneiro, E. Morello, and G. Desthieux. Assessment of solar irradiance on the urban fabric for the production of renewable energy using lidar data and image processing techniques. In Advances in GIScience, pages 83–112. Springer, 2009.

7. C. Carneiro, E. Morello, T. Voegtle, and F. Golay. Digital urban morphometrics: automatic extraction and assessment of morphological properties of buildings. Transactions in GIS, 14(4):497–531, 2010.

8. N. Lukac, S. Seme, D. Zlaus, G. Stumberger, B. Zalik. Buildings roofs photovoltaic potential assessment based on (Light Detection And Ranging) data. Energy 66 (2014) 598-609.

9. D. Assouline, N. Mohajeri1, J.-L. Scartezzini. A machine learning methodology for estimating rooftop photovoltaic solar energy potential in Switzerland. Proceedings of International Conference on Future Buildings & Districts Sustainability from Nano to Urban Scale. Volume II, 9 – 11 September 2015, EPFL Switzerland.

10. J. Gooding, R. Crook, A. S. Tomlin. Modelling of roof geometries from low-resolution LiDAR data for city-scale solar energy applications using a neighboring buildings method, Applied Energy 148 (2015) 93–104.

11. M. Kada, Scale-dependent simplification of 3D building models based on cell decomposition and primitive instancing. In: Proceedings of the International Conference on Spatial Information Theory. COSIT'07. Melbourne, Australia 2007. pp. 222–237.

12. C. Cortes, V. Vapnik, Support-vector networks. Machine Learning, 20(3):273–297,1995.

13. A. Hur-Ben, J. Watson. 2010. A user's guide to Support Vector Machines. Methods Mol Biol. 2010; 609:223-39. doi: 10.1007/978-1-60327-241-4_13.

14. T. Hastie, R., Tibshirani, J. Friedman. 2013. The Elements of Statistical Learning: Data Mining, Inference, and Prediction. Springer Series in Statistics, USA.

G. Habert, A. Schlueter (eds.): Expanding Boundaries © 2016 vdf Hochschulverlag AG an der ETH Zürich
DOI 10.3218/3774-6_21, ISBN 978-3-7281-3774-6, http://vdf.ch/expanding-boundaries.html