Clustering methodology for defining a short test sequence for whole system testing of solar and heat pump systems

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Abstract

Dynamic whole system testing methods are currently applied to evaluate the performance of heating and cooling system. One major obstacle to the implementation of such dynamic test methods is the cost connected to the experimental phase. To define a short test sequence, an original implementation of "k-medoid" clustering has been implemented. The paper investigates on the length of the sequence and how the days should be described to achieve effective results. A family of solar assisted heat pump systems has been generated by varying the collector field area and storage tank volume and studied via numerical simulations.

The results show that the days can be described as a function of average temperature and global horizontal irradiation. The simulation of different sequence lengths shows that a six-day sequence can be used to test the system with a possible deviation of results lower than 8% if compared to the annual simulation. The deviation is reducing with a higher number of clusters.

Keywords: Clustering; short test sequence, solar and heat pump system.

1. Introduction

In the contest of reducing the heating and cooling consumption, the system efficiency plays an important role. In a complex system composed by different energy sources and variable distribution, often driven by renewable energy, the performance of the entire system does not correspond to the "sum" of the single components performance, as the way the components interact among themselves has itself an impact on the performance and needs to be correctly considered. For this motivation, dynamic methods capable of assessing entire systems are used to characterize the system performance by different research institutes (Haller et al. 2013). The main advantage of this method is that the entire system is installed in the test chanber and realistic working conditions are used to study its performance. In this way, it is possible to perform a reliable evaluation of the system performance as-a-whole.

To reduce the cost of experimental phase, short test sequences (between 6 to 12 days) are defined to represent the seasonal boundary conditions. To arrange such short sequence, the literature presents different methodologies:

- Iterative definition of the sequence with the aim of attaining proportionality to the annual performance.
- Selection of days with temperature and radiation profiles corresponding to the monthly average conditions.
- Selection of days using some sort of weather data classification.

In the first approach, an optimization program reduces the deviation between the test bench data and the annual simulation of a system model. In addition to the fact that the method relies directly on a model of the system, it requires to perform a different optimization for every weather condition required to reproduce the weather pattern at the given location (unless the test it is referred to only one condition). The second approach is more easy to be implemented but in some cases it could not be able to perform a direct evaluation of performance, see for example (Haberl et al., 2009). For the last approach, different methodologies can be identified, i.e. classification into bins or classification with clustering. For example, the clustering has been adopted also for the definition of short sequence for the simulation of combined heat and power systems (Domínguez-Muñoz et al. 2011) and for heat pump systems (Huchtemann et al. 2016).

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In the development of the PLPE procedure (Menegon et al. 2017), we have investigated different methodologies. The first option was to create classes in according to the procedure developed for the test of components (Menegon et al. 2014). The method organizes the boundary conditions into multidimensional classes and a proportional part of the so-obtained distribution is selected. The good results obtained for the component test were not replicable when applied to the entire systems. Therefore, we decided to explore other techniques. Clustering, among the options we have considered, has the advantage that the weather conditions are classified without performing model simulations. In addition, the sequence corresponding to a certain climate can be easily be calculated. This study employs extensively numerical simulation of entire systems to verify the validity of the selections performed with clustering.

In particular, section 2 presents the clustering methodology while its application to the definition of test sequences of different duration is presented in the section 3. Different sequences are defined for the climate of Bolzano and Zurich. The section 4 presents the SAHP system to which the clustering procedure has been applied. The results and concluding remarks are finally given in section 5.

2. Method

The purpose of clustering is to group a set of objects in such a way the objects in the same group (called cluster) are closer, or more similar, to each other more than to those in other groups. In other words intra-cluster similarity is higher than inter-cluster similarity. In the case of this application, the objects to be classified are the days of a given weather file (long one year). The literature presents different algorithms and the authors have applied the Partitioning Around Medoids (PAM also called k-medoids) algorithm et al. 2007).

The user selects a number of clusters “N” and the algorithm classifies the objects into the “N” clusters. To apply the algorithm, the objects need to be described by a number of numerical variables, which are used to map every objects into a point in an M-dimensional coordinate space. Sometimes, the geometrical representation can be used to graphically represent the objects in the clusters.

The algorithm starts by defining randomly “N” initial medoids and the initial clusters are computed assigning every point in the cloud to one of these clusters. The clusters boundaries are then modified following an iterative process that tries all the possible combinations of point and cluster. The final clusters outline is obtained minimizing the total Euclidean distance between the cluster points and the medoid of the cluster they belong to. As the unit of measure used to characterize the objects along the dimension are different, data is usually moved (removing the mean) and scaled (by the reciprocal of the standard deviation) to avoid unit of measure bias. In this way, the object could be described by variables of different normalized physical quantities.

At the end of the iterative process, the “N” clusters are produced and the representative objects should be selected. Both the centroid and the medoid could represent the cluster: the centroid is the geometric center while the medoid is the nearest object to the centroid. For a discrete dataset, the centroid could not be part of the dataset. As in our case the points represent day of the years, the sequence is created selecting the medoids.

To understand better the application of the method, an example of classification of events with the clustering is given in Table 1: 15 objects, representing day of the year described by their mean temperature and irradiation, were randomly generated. Willing to select 3 representative days out from these 15, the method divides the objects into 3 clusters and then we select as representatives the clusters medoids.

Tab. 1: Example of clustering. 15 objects with their characteristics and cluster identity.

Day	Temperature [°C]	Irradiation [Wh/m^2]	Cluster
1	1.91	2376.85	0
2	9.90	2694.12	1
3	5.98	751.26	1
4	8.86	5.65	1
5	0.14	1048.74	0

6	2.57	1929.99	0
7	4.30	210.95	0
8	0.45	161.38	0
9	8.64	1454.36	1
10	0.58	5923.16	2
11	0.69	4057.67	2
12	3.77	6457.90	2
13	3.72	2715.89	0
14	6.00	4473.34	2
15	0.95	4764.96	2

Figure 1 shows the graphical representation of clusters indicating with different colors the different clusters. The centroids are indicated with a yellow point and the medoids are encircled. The centroids can be quite far or very close to a member of the dataset but usually they do not belong to the dataset. In this example, the sequence would be created with the temperature and irradiance profiles of objects 6, 9 and 15.

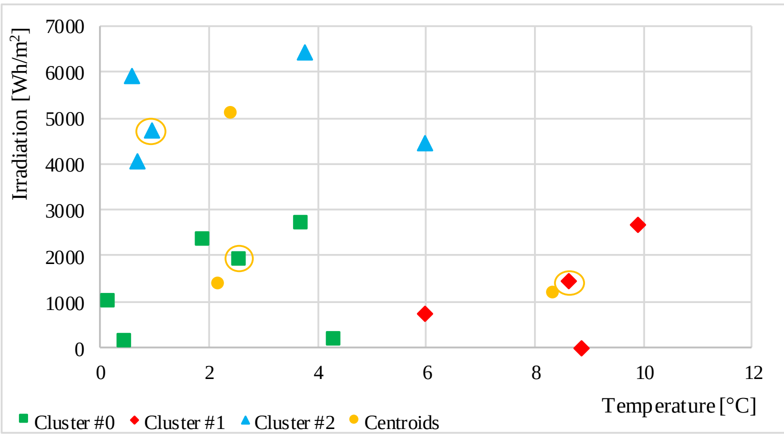

Fig. 1: Six-day and ten-day sequence defined with clustering of the climate of Bolzano.

In our procedure, the annual performance is directly extrapolated from the sequence performance, that is the performance of the tested system under the boundary conditions assembled from the short sequence. As the number of objects per cluster is usually not the same, the extrapolation of seasonal performance is done weighing the energy performance on the specific day by the size of the clusters it belongs to:

$$Q_{seas} = \sum_{i=1}^{n_{cluster}} n_{el,cluster,i} \cdot Q_i \qquad \text{(eq. 1)}$$

Where Qi is the energy measured during the event corresponding to the i-th Medoid and $n_{el,cluster,i}$ is the size of the i-th cluster, i.e. the number of objects it contains. The equation is valid for the thermal energies (SH, SC, DHW, collector and so on) and for the electric consumptions.

The medoid load is not equal to the cluster average load. In this way, the eq.1 does not give exactly the cluster load energy. In the PLPE method, the load is fixed and therefore we can apply a scaling factor to the medoid load. This factor (one value for each cluster) compensates for the deviation between the medoid energy and the cluster average energy.

$$L_{sc(i)} = \frac{E_{Simulations.Day(i)}}{E_{Simulations.Cluster(i)}} \cdot N_{Days.In.Cluster(i)} \qquad \text{(eq. 2)}$$

The scaling factor (Lsc) scales the space heating space cooling loads. The scaling factor is lower when a 3D or 4D coordinates are used then a 2D coordinate system.

The sequence defined with clustering would be closed to a correct representation of the whole year performances when the performances are linearly dependent from the boundary conditions. This because the days are selected considering the nearest object of geometric center of each cluster and the consumptions and loads are built through discrete integration.

As example, considering one-dimensional case where the consumption (W) is linearly dependent from the temperature, the consumption can be described as:

$$W = \alpha \cdot \mathrm{T} + \beta \qquad \text{(eq. 3)}$$

Where the parameters α and β are the coefficients of the linear dependence.

The total consumption is a sum of the “i-th” consumptions, and each “i-th” consumptions could be described as a function of the “i-th” temperatures with the equation:

$$W_{tot} = \sum_{i=1}^{N} W_i = \sum_{i=1}^{N}(\alpha \cdot T_i + \beta) = \alpha \cdot \sum_{i=1}^{N}(T_i) + \beta \cdot N \qquad \text{(eq. 4)}$$

In this case, the geometric center corresponds to the average temperature and the last summation could be substituted with the average temperature multiplied by the number of objects:

$$W_{tot} = \sum_{i=1}^{N} W_i = (\alpha \cdot \bar{T} + \beta) \cdot N \qquad \text{(eq. 5)}$$

The total consumption could be calculated directly from the geometric center of the boundary condition (in this case one temperature). The same demonstration could be performed with a multi-dimension problem when the consumptions are linearly dependent from more boundary conditions.

3. Short Sequence

As we have seen in the methodology section, the days have to be compared in terms of some characteristics that became the coordinates for the method. Days can be characterized by profiles of temperature, irradiance (with its different components), relative humidity, wind speed and so on. Not all these variables have the same influence on an heating and cooling system performance. For example, in a SAHP system the temperature and the irradiance profile have a higher effect than the wind speed. To reduce the number of variables that identify an object, the average ambient temperature and total irradiation on the horizontal surface are considered, describing a 2D coordinates. This classification is the simplest possible. Other solutions are given by adding the space load to the classification. Other options could be using 3D and 4D clustering where the 3D clustering considers the temperature, irradiance and heating and cooling load (in one vector using the sign to discriminate between heating and cooling), while the 4D considers the temperature, the irradiance and the heat and cooling loads separately.

In addition, the sequence length should be determined. The results presented in the literature show that longer sequences are more representative of the whole season. However, it is important to remark that the sequence length is a trade-off between accuracy and cost. To verify the influence of the sequence length in our application, we defined sequences of 6, 8, 10, 12 and 24 days.

In this study, we present the results for the climates of Bolzano and Zurich. The sequences are used as boundary condition of a family of reference numerical models of a solar assisted heat pump system (SAHP). The reference models were generated by varying, the collector area and the tank storage volume.

Fig. 1 shows the effect of changing the number of clusters: six clusters (green triangular points) and ten clusters (red diamonds points). With a different number of cluster, the shapes of the clusters changes and therefore different days are selected. It is possible that one specific day is selected by both classifications, although this is not generally the case (in the figure, one triangle - with coordinates 22°C, 7322 Wh/m^2 - is hidden by one diamond). With a larger number of clusters, a wider range of temperature and irradiation are covered. This happens because the dataset is relatively uniform and therefore medoids are quite uniformly distributed which means that increasing their number will cover better points at the boundary of the dataset. The other way round, with only few cluster the extreme conditions could not be reached.

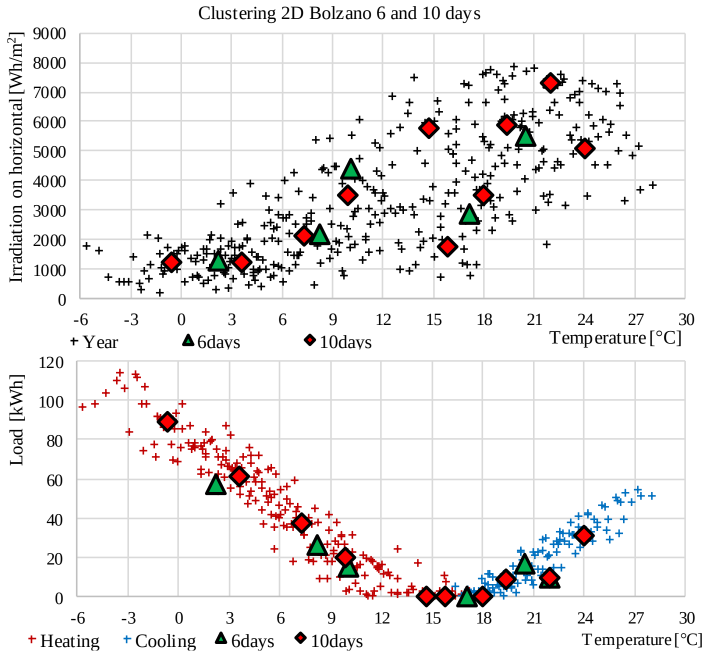

Fig. 2: Six-day and ten-day sequence defined with 2D clustering of the climate of Bolzano.

Fig. 2 shows the identification of the sequence for Zurich. The green triangular points identify the selection with 2D coordinates (T and GHI), the red diamonds points identify the selection with 3D coordinates (T, GHI and Load) and the blue circle points identify the selection with 4D coordinates (T, GHI, Heating and cooling load). The figure in the left shows the days of the year as function of the average temperature and global horizontal irradiation while the right figure shows the days as a function of the average temperature and the space load distinguished into cooling (blue points) and heating (red points).

The different coordinates of the days (2D, 3D, 4D) modify the geometry of the problem and therefore the selections are different.

In the climate of Zurich, the 2D clustering does not considers days with space cooling load. The 3D clustering selects only one day with very low load (1.6 kWh) while the 4D clustering selects two days with cooling load (one with 1.6 kWh and the other one with 25.5 kWh). The reason for this fact is that only few events require cooling. Using the 2D clustering, the load is more influenced by the temperature and irradiation while the 3D clustering gives more importance to the load. The 4D clustering gives equal importance to the cooling and heating load since the coordinates are normalized. This means that in a climate like Zurich where the heating load is about 30 time the cooling load, this selection would give the same number of days to the heating and to the cooling season, resulting in an unbalanced selection.

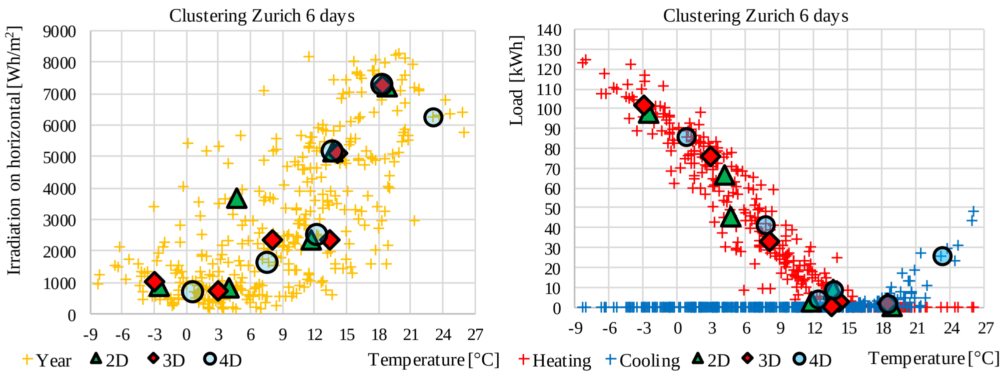

Fig. 3: Identification of six-day sequences defined with different coordinates. Zurich climate.

In addition to the information given with previous figures, Fig. 4 shows how the 2D and 3D coordinate systems affect the boundary conditions profiles. The figure present the two six-day sequence defined in the climate of

Bolzano. The 2D clustering presents the temperature profile higher than the 3D clustering and as consequence the heating load is lower and the cooling load is higher. The temperature profiles are smoothed between two days.

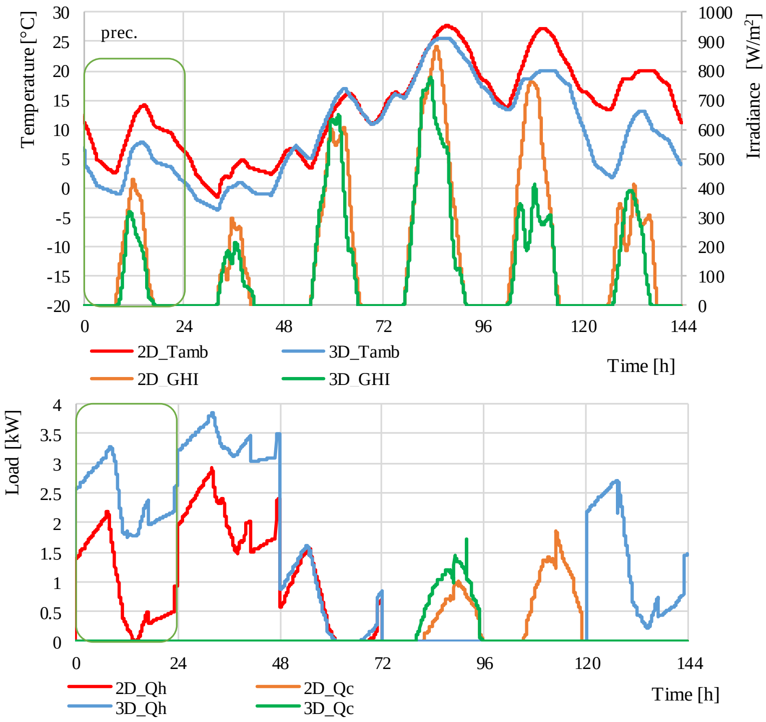

Fig. 4: Comparison of six-day sequences profiles defined with different 2D and 3D coordinates. Bolzano climate.

4. Simulation

The clustering was tested simulating a family of SAHP systems (see figure 5). The study considers different configurations of collector area (8 m^2 or 16 m^2) and storages volume (700 l or 1500 l). The volume of 700 l is obtained connecting in series a 500 l and a 200 l storages while the 1500 l volume is obtained with the combination of a 1000 l and 500 l storages.

The system was modelled with Trnsys (Klein and et al. 2012) and the components were validated with laboratory tests or with monitoring data (Bettoni 2013). The figure presents the layout and the models of the system:

- The heat pump model (type 847) is based on a performance map (as a function of inlet temperatures and flows).
- The collector model (type 1) considers the collectors' parameters calculated in the certification test of one commercial collector. The type 1 is coupled to a moving average to introduce inertia effects.
- The Storages model (type 340) is a commercial type (Drück and Pauschinger 2006).
- The building model is type 56.
- The weather file is read with the type 109 for the simulation of the whole year. The sequence' weather data is read with type 9.
- The dry-cooler model (type 880) was developed by (Besana 2009; Bettoni 2013).
- Other traditional models are the pipes (type 31), circulation pump (type 110), mixing and tempering valves (type 11) and heat exchanger (type 5b).

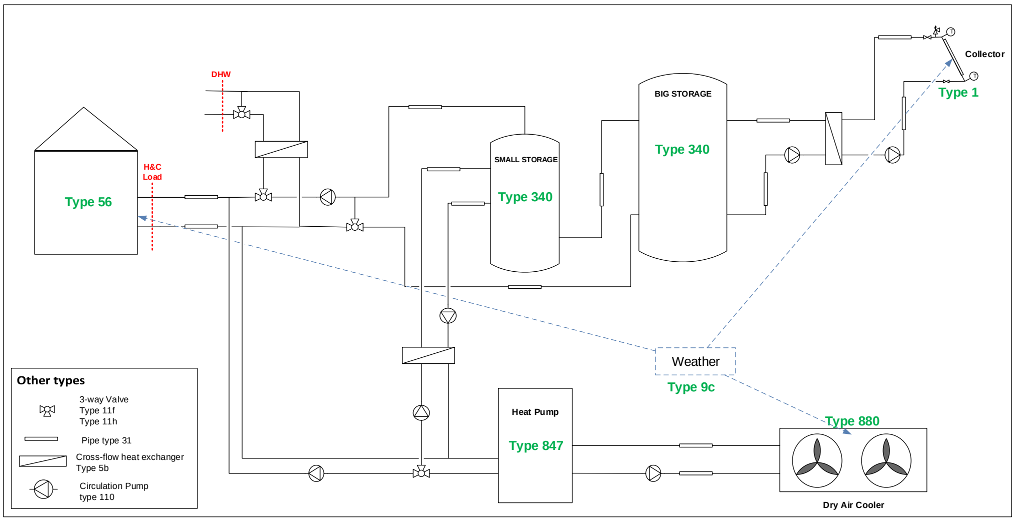

Fig. 5: System layout and component models.

The sequences are the boundary condition for the simulation of this system. The selection with the clustering method does not give any advice on the order of the sequence. The days are ordered in the same order as they occur in the year starting from the winter and ending the sequence with the autumn conditions. The last day of the sequence is used to precondition the whole sequence.

The simulation set-up considers the combination of:

- Climates of Bolzano and Zurich.
- 6, 8, 10, 12 and 24 day.
- 2D, 3D and 4D coordinates.
- System configurations (collector area and storage volume).

In parallel to the sequence simulation, also the whole year was simulated. The values extrapolated from the short sequence are compared with those calculated from annual simulation. The deviation between the values extrapolated from the short sequence and the annual simulation with:

$$\delta X = \frac{X_{short\ sequence} - X_{annual\ simulation}}{X_{annual\ simulation}} \qquad \text{(eq. 6)}$$

Where X represents one of the selected performance figures among thermal energy (load or source), electrical consumption, seasonal performance factor and solar fraction.

Six-day sequence are defined also for Rome and Gdansk.

5. Results

Figure 6 and Figure 7 show the SPF deviation (eq.6) as a function of the number of clusters for the climate of Bolzano and Zurich for the different plant configurations. The figures show the total SPF value calculated with the annual simulation. In general, the deviation of SPF decreases as the number of clusters increase. Table 2 and Table 3 report the SFP deviation RMSD and span (the difference between the maximum and minimum value). These values help to understand how much the trend could variate by selecting a different number of clusters. The cells of the two tables are colored in order to highlight in green the smallest values (best case) and in red the highest values (worst case).

The first outcome, is that the 4D clustering presents the highest deviation. As it was noticed before discussing the points in figure 3 (section 3), the 4D coordinate system gives an unbalanced selection (the days with heating load have the same weight as the days with cooling load also if the two loads are different). The 2D clustering represents better the selection in the climate of Zurich while the 3D represents better the selection in the climate of Bolzano.

The second outcome is that the configuration with the 700 l storage has a lower deviation than that with the 1500 l storage while the configuration with 8 m^2 of collector has a lower variation than the case with 16 m^2. In general, we expect the sequence to be less accurate in case of high collector area. In the short sequence, more consecutive days with high irradiation could not be present while it occurs during the summer season. In this case, the stagnation could be neglected by the short sequence because the storage does not have enough energy to stagnate. Besides the effect of collector area, also the effect of the storage volume has to be considered. If we examine the extreme case of high collector area and very low storage volume, the system would use the solar energy by the end of the day when it has been produced since the solar energy cannot be stored. Therefore, a short sequence could be representative since no stagnation occurs due to consequent days with high irradiation. Increasing the volume, this effect starts to be noticeable. In fact, all the sequences simulated for the case of system with 700 l are more accurate than those with 1500 l.

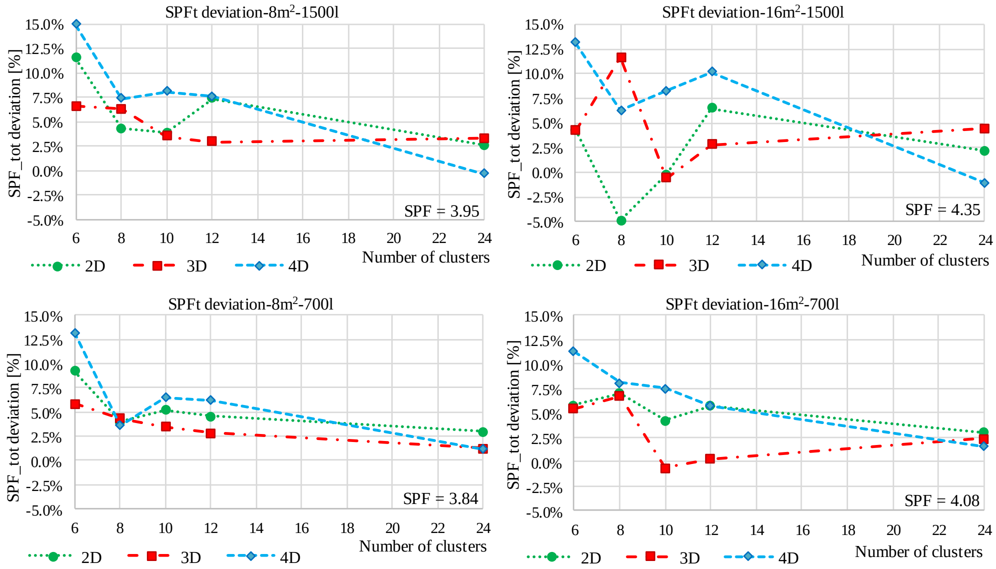

Fig. 6: Total seasonal performance factor as a function of the number of cluster and M-dimensional coordinates. Simulation of a SAHP system with different collector field and storage volume. Bolzano Climate.

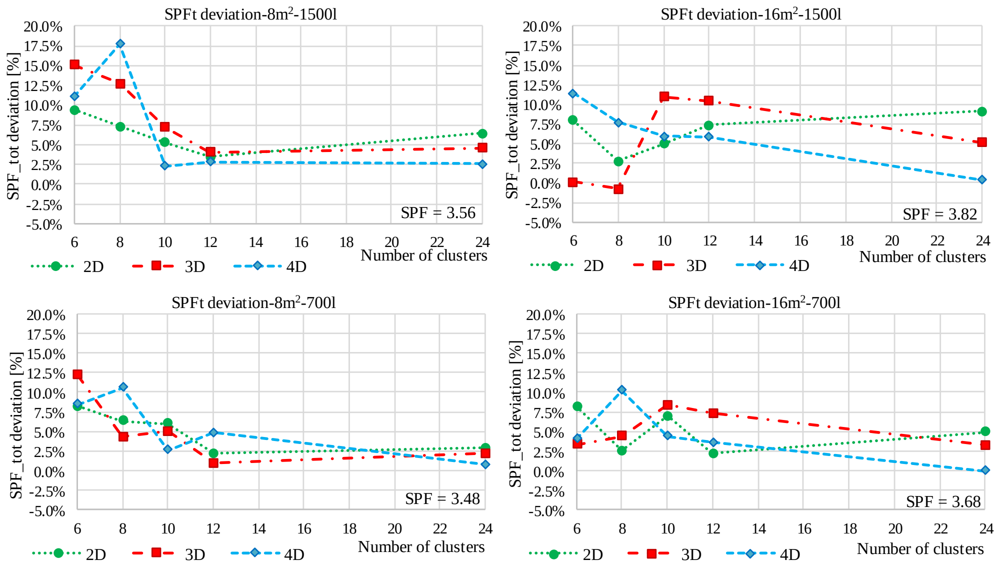

Fig. 7: Total seasonal performance factor as a function of the number of cluster and M-dimensional coordinates. Simulation of a SAHP system with different collector field and storage volume. Zurich Climate.

Tab. 2: RMSD in the different coordinate systems.

		2D	3D	4D		2D	3D	4D
Climate	**Stor.\Size**	**8m²**	**8m²**	**8m²**		**16m²**	**16m²**	**16m²**
BZ	**1500**	6.7%	4.8%	9.0%		4.2%	6.0%	8.8%
ZU	**1500**	6.7%	9.8%	9.6%		6.9%	7.2%	7.2%
BZ	**700**	5.2%	3.9%	7.3%		5.4%	4.1%	7.6%
ZU	**700**	5.6%	6.3%	6.5%		5.5%	5.7%	5.5%

Tab. 3: RMSD in the different coordinate systems.

		2D	3D	4D		2D	3D	4D
Climate	**Stor.\Size**	**8m²**	**8m²**	**8m²**		**16m²**	**16m²**	**16m²**
BZ	**1500**	0.35	0.14	0.6		0.5	0.53	0.62
ZU	**1500**	0.21	0.39	0.55		0.24	0.45	0.42
BZ	**700**	0.24	0.16	0.46		0.16	0.3	0.4
ZU	**700**	0.21	0.39	0.34		0.22	0.19	0.38

The system considered in this study presents the possibility to satisfy the space heating and domestic hot water loads with the solar energy or the heat pump, while the space cooling is satisfied only with the heat pump. The cooling SPF does not depends from the collector area and the storage volume and in the climate of Bolzano is quantified in 4.22. The figure 8 presents the trend of the deviation of the cooling SPF. This figure presents the same scale of the ordinate axis of figure 6 to show that the variation of cooling SPF is much lower than the total SPF and the deviation could be considered not dependent from the number of clusters. The reason is that the performance of the heat pump is close to be an affine dependence of the air temperature. We have shown with eq.3 to eq.5 that the clustering is nearly optimal in such a case.

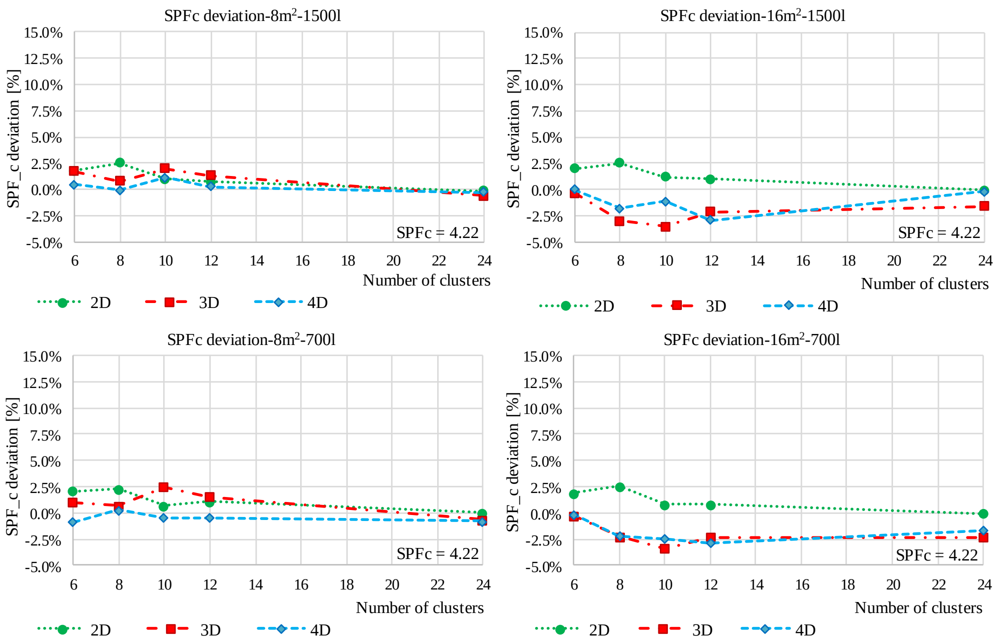

Fig. 8: Total seasonal performance factor as a function of the number of cluster and M-dimensional coordinates. Simulation of a SAHP system with different collector field and storage volume. Bolzano Climate.

Regarding the solar fraction, figure 9 presents the result of Zurich. The solar fraction is well reproduced for lower storage volume or collector area. The clustering with a 2D selection represents better the solar fraction with the only exception of Zurich with 16 m^2 and 1500 l (the sequence deviates from the annual simulation about 10 %). The cooling solar fraction is 0 since the plant uses only a compression chiller and not thermally driven chillers.

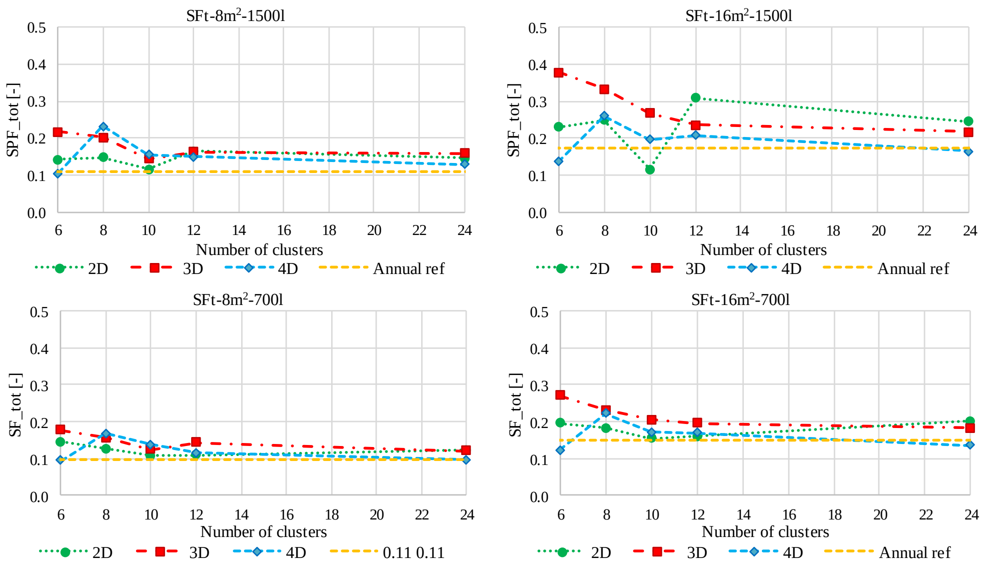

Fig. 9: Total solar factor as a function of the number of cluster and M-dimensional coordinates. Simulation of a SAHP system with different collector field and storage volume. Zurich Climate.

A shorter sequence is more attractive in terms of the cost connected to the testing phase but presents the highest uncertainty. In any case, the results presented previously showed that 2D or 3D coordinate system have a deviation lower than 10% with respect to the annual simulation. The 2D clustering was used to define a six-day sequence for other climates. Table 2 presents the total seasonal performance factor calculated with six-day sequence and with the annual simulation. The climates considered are Bolzano, Zurich, Gdansk and Rome. The highest deviation is 7.85% obtained for the climate of Zurich while the lowest deviation was obtained for the Roman case. This lower deviation could be also explained by the smaller collector area (16m^2 were not considered in this case since it would have not represented a good system design).

Tab. 4: Deviation of total SPF of six-day sequences defined with 2D clustering.

	Bolzano 16m²-1500l	**Zurich 16m²-1500l**	**Gdansk 16m²-1500l**	**Rome 8m²-1500l**
Six day	4.43	4.12	3.85	4.79
Annual	4.21	3.82	3.62	4.82
Deviation [%]	5.22%	7.85%	6.35%	0.62%

6. Conclusion

The purpose of this paper is to clarify the methodology used in the PLPE procedure to define a short test sequence starting from the annual weather data. The PLPE procedure is a method to perform dynamic test of entire heating and cooling systems in an objective way which is easily applicable to different climates and that allows a direct extrapolation of the seasonal results from the short test.

The underlying tool at the heart of the procedure is clustering. The days are grouped into clusters wherein each object is more similar to each other than to those in other clusters. To build the sequence, for each cluster, the medoid, i.e. the closest object to the geometric centre, is selected. The days can be described with different quantities and the optimal solution is to consider the daily average temperature and the daily irradiation on horizontal surface. In the sequence, the days are ordered with the same order they occur in the year starting from the winter days and concluding with the summer days.

The sequence defined with clustering represents correctly the seasonal performances when those are linearly dependent to the boundary conditions; this could be a good approximation of heat pump system while for solar system the performances are not linearly dependent from boundary conditions.

Different system configurations have been simulated with sequences of different sizes. The deviation of the seasonal performance figures calculated with the short sequence and compared with the ones calculated with an annual simulation decreases as the number of clusters is increased. To that, we have noticed an influence on the accuracy given by the collector area and the storage volume. The deviation between the short sequence performance and the annual performance increases with increasing the collector area and the volume of storage.

A six-day sequence defined with 2D clustering has been defined for the climates of Bolzano, Zurich, Gdansk and Rome and the expected deviation is lower than 8%.

The main advantage of adopting the clustering is that the simple application of the methodology does not require any iterative simulation and therefore a test sequence can be defined for each climatic condition where the test would be performed.

The clustering could be used also for reducing the computational time for large parametric simulations. In that case the user can chose the proper number of clusters.

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