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DATA-DRIVEN MODELLING OF THE ENERGY CONSUMPTION OF AIRPORT CITIES

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Abstract

The airport city of Vienna International Airport consists of more than 125 energy-consuming objects – mostly buildings but also infrastructure. In order to ensure their energy-efficient operation, digital models are needed that predict the energy consumption that the objects should have. Multiple linear regression can provide such models if historical data is available to train regression models with. In our approach, we explore how regression models must be set up for the case of airport objects. Further, we investigate how the prediction performance of multiple linear regression can be improved by combining it with other methods.

Introduction

Airports such as Austria’s largest airport, Vienna International Airport, are comparable to small cities in terms of size, energy consumption, and complexity.

While the term “airport” generally refers to the buildings and infrastructure that are necessary to provide aeronautical services, the term “airport city” also refers to buildings and infrastructure in relatively close proximity that interact with the airport (Kasarda, 2006).

The whole Vienna airport city consists of more than 125 objects that are connected to and supplied by the airport’s electricity grid, heating grid, or cooling grid. Most of the objects are separate buildings, some are parts of the general infrastructure (e.g. the apron lighting), and some are a set of buildings that share the same energy meter. In the past years the operator of the Vienna International Airport, the “Flughafen Wien Aktiengesellschaft”, initated several projects that aim for the reduction of the energy consumption in the airport city. For instance, in the project “Virtuelle Flughafen Stadt” (Virtual Airport City) a virtual model of the airport city regarding to energy-consumption was created (Forster et al., 2018). In the project “Smart AirportCity” an energy monitoring system was established in order to collect the airport city’s energy meters in one single system (Lindinger et al., 2020).

The overall goal of such projects is to identify abnormal energy consumption and ensure an energy-efficient operation of buildings and infrastructure to avoid unnecessary waste of resources. For this purpose, the normal daily consumption must be known, and due to the large number of objects in airport cities, the creation of detailed consumption models (e.g., models that can be used for hygrothermal building simulation) is not feasible. Therefore, there is the need for another type of model that indicates nominal energy consumption based on historical data, the so-called data-driven model.

The research field of machine learning offers several methods for data-driven modelling – each of them with their unique advantages and disadvantages. One of the most basic methods is the multiple linear regression. Its simplicity, its speed, and the fact that it is not some sort of black box or dependent on random processes are its main advantages (Hastie et al., 2017). By using multiple linear regression with the method of “one-hot enconding”, it is possible to achieve remarkable prediction performances (Price, 2010, Granderson & Price, 2012). In building science multiple linear regression models with a certain type of “one-hot encoding” are often known as LBNL (Lawrence Berkeley National Laboratory) models. In those models the timestamp information is translated to a set of “time-of-week” indicators. Basically, the time and the weekday of each datapoint are “one-hot encoded” (Price, 2010).

In our approach, we show which predictor variables are useful to model the energy consumption of objects in the airport city. For this purpose the prediction performance of LBNL models and four alternative models, which facilitate multiple linear regression but do not use “one-hot encoding”, are evaluated.

Method

To build multiple linear regression models that can predict the course of energy consumption of objects, time series of their energy consumption and parameters to be used as predictor variables are needed. As the heating and cooling energy consumption of buildings is primarily determined by weather conditions, the time series should cover a period of time that includes all the different weather conditions that normally occur at the location of the facilities, i.e., at least one full year.

Thus, for the analysis of the energy consumption of airport cities, we now take the weather data and 15 min load profiles from the objects of the airport as basic data set. This data set is extended by additional time-related information that is known to influence the intensity of aeronautical services and therefore the energy consumption of certain objects:

- Time – the Central European Time or the Central European Summer Time encoded as categorical variable with 15 min time resolution steps resulting in 96 possible values: 00:00, 00:15, …, 23:30, 23:45
- Weekday – the day of the week encoded as categorical variable with 8 possible values: Monday (1) to Sunday (7) and Holiday (8)
- Bridge day – information whether the day is a bridge day or not encoded as binary variable: Normal day (0) and bridge day (1)
- Free – information whether the day is part of the school holidays or not encoded as binary variable: No school holiday (0) and school holiday (1)
- Flightplan – information whether the Airport's winter or the summer flightplan was valid during this day encoded as binary variable: Winter flightplan (0) and summer flightplan (1)

The weather data consists of the following variables:

- Temperature – the air temperature in °C
- Radiance – the global horizontal radiance in W/m²
- Humdidity – the relative humidity in %
- Pressure – the atmospheric pressure in hPa
- Rain – information whether it was raining or not encoded as binary variable: No rain (0) and rain (1)

The time- and weather-related data are used as a training set for five different regression models (ATR, RT, RiT, ARiT, LBNL), which are examined for their applicability in terms of load profile prediction. In the following, we describe the general approach for the training of and prediction with the models and then their specific application steps.

While the LBNL models are plain multiple linear regression models with one-hot encoding, the other types of models are combinations of multiple linear regression with two other methods (filtering, averaging). These combination models are basically a step-wise application of the same methods in different orders. After one method is applied on a load profile, it is immediately used to predict the same load profile. The difference between the input load profile and the predicted load profile, the "residual load profile", is then used as input for the next method. The idea behind this step-wise approach is that different methods can grasp different aspects that influence the load profiles. While the multiple linear regression primarily models the influence of the weather, the other methods model the temporal aspects.

In order to predict energy consumption with these combination models, the steps are simply reversed and the outputs of the respective methods added to form the predicted load profiles. To ensure that the predictions stay in a plausible range, they were limited to the minimum and maximum values that were present in the training data set of a load profile.

The heart-peace of every model is the multiple linear regression, which is trained to predict a load profile or a residual load profile. Here the weather data variables and the variable "bridge day" are used as predictor variables. If interaction between those variables is allowed, the token in the model name is "Ri", otherwise it is "R". In order to predict with the multiple linear regression, it is simply provided with new weather data and the information whether the day is a bridge day or not.

The first combination method is the calculation of the average daily load profile. This average daily load profile is calculated out of all days that are present in the training data set – regardless of the weekday or other time-related information. If this method is used, the token in the model name is "A". In order to predict with this method, it must be provided with information about the time and then the corresponding average load profile value is returned.

The second combination method is the calculation of the average daily load profile for each type of day. To accomplish this, the training data is filtered for each possible combination of the variables "weekday", "free", and "flightplan". An average daily load profile is then calculated for each of these 32 types of days. If this method is used, the token in the model name is "T". In order to predict with this method, it must be provided with the information of the variables "weekday", "free", "flightplan", and the time and then the corresponding average load profile value of the respective type of day is returned.

ATR model

1. The average daily load profile (A) is calculated out of one load profile.
2. The "residual load profile" from step 1 is then filtered according to each type of day

and the average load profile for this type of day is calculated (T).

3. A multiple linear regression without interaction (R) is then trained to predict the "residual load profile" from step 2.

RT model / RiT model

1. A multiple linear regression without interaction (R) or with interaction (Ri) is trained to predict one load profile.
2. The "residual load profile" from step 1 is then filtered according to each type of day and the average load profile for this type of day is calculated (T).

ARiT model

1. The average daily load profile (A) is calculated out of one load profile.
2. A multiple linear regression with interaction (Ri) is then trained to predict the "residual load profile" from step 1.
3. The "residual load profile" from step 2 is then filtered according to each type of day and the average load profile for this type of day is calculated (T).

LBNL model

The LBNL model is simply a multiple linear regression model, where the variables "time" and "weekday" are one-hot encoded and all other variables are used as-is.

Model selection

The application of the five models was carried out on the objects of the Vienna International Airport. The models were trained with synthetically generated load profiles for three types of energy (heating, cooling, electricity), which were originally derived from energy meter data from 2016. Since the 2016 data consists only of detailed energy readings with a temporal resolution of 15 min for certain nodes of the supply grid infrastructure (e.g., transformers) and otherwise monthly energy meter readings, synthetic load profiles (15 min resolution) were calculated from these detailed load profiles, the monthly readings, and additional information (e.g., which object is connected to which node) (Lindinger 2020). The training data used to develop the models is almost the whole data set from 2016. The only data that is not included are the days that were semi-randomly sampled for the test data set. For each possible combination of the variables "weekday", "free", and "flightplan" one day was randomly sampled from the days that fit the combination. This led to a test data set encompassing 32 days and a training data set encompassing 334 days.

All available load profiles of all airport city objects are modelled for each type of model. The prediction performance of all five types of models is estimated through repeated random subsampling validation (100 repetition cycles).

Results

Figure 1 shows the prediction performances that the five models achieved during the 100 repetition cycles. Every model was trained and evaluated with data from each of the 198 load profiles (124 electricity, 20 cooling, and 54 heating) – i.e. the boxplot of each model is based on 19.800 values.

The prediction performance is presented by two indicators, namely the coefficient of determination (R^2) and the deviation of the cumulative predicted consumption from the cumulative real consumption (short: deviation).

Due to the calculation method for synthetical load profiles of 2016, the load profiles of smaller objects appear to be random noise instead of showing a distinct daily pattern. Thus, the prediction performance is especially poor when predicting such small objects. To compensate for this, Figure 1 is extended by an additional view, in which only the prediction performance of the larger objects, that are responsible for 95% of the respective energy consumption, are shown. In this view the number of values the boxplot of each model is based upon declines to 9.600. A comparison of this view with the original view shows that there are less outliers and that generally, the prediction performance increases. When analyzing the deviation, it becomes obvious that, regardless of the model type, with a 99.7% confidence the deviation will approximately be between -9% and 10% (95% view: -8% and 8%). Moreover, in 50% of the cases, the deviation can be expected to be between -2% and 3% (both views). I.e. even if the prediction of a load profile does not match the daily pattern, the cumulative predicted energy consumption is not too far off.

The R^2 score can come from a much broader band of possible values. While most of the values can be expected to be in a range between 0.5 and 0.8, the range extends from near 0.0 and 1.0 at a 99.7% confidence interval. Some outliers are even below 0.0, indicating that in those cases the predictions are worse than random. Considering the origin of the synthetical load profiles and the fact that the number of outliers is low enough to be deemed insignificant, these results do not void the usefulness of the prediction models. When comparing the R^2 scores of the different models in Figure 1, it becomes obvious that the prediction performance of the ATR model is slightly below the performance of the LBNL model. Contrary to that, the RT, RiT, and ARiT models show a slightly better performance.

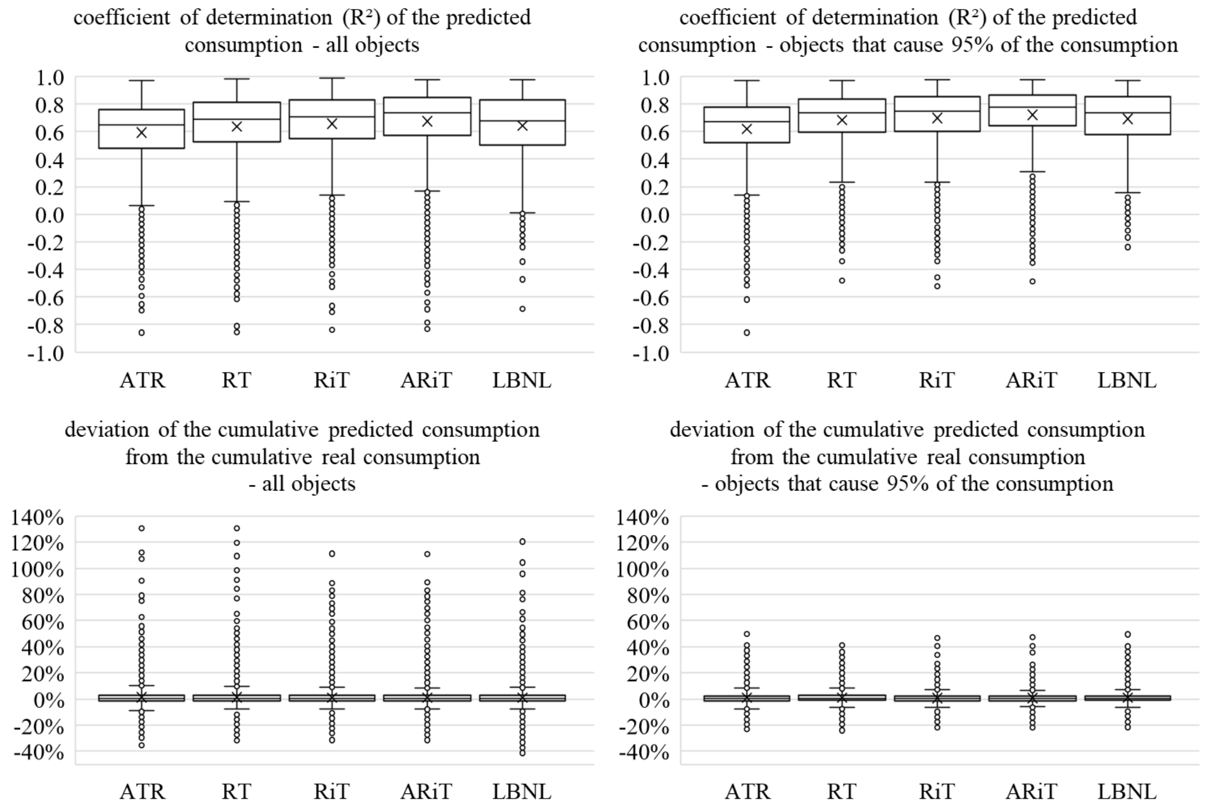

Figure 1: Boxplots of the prediction performances that were achieved by each of the five multiple linear regression model types when predicting the energy consumption of the airport cities' objects during 100 cycles of repeated random subsampling

The prediction performances that each model achieved during the 100 repetitions were averaged for each load profile and ranked in order to determine which model should be used to predict the load profile of one object and energy type. Table 1 and 2 illustrate the results of this ranking. While Table 1 shows the results of a ranking according to the coefficient of determination, Table 2 shows the results of the ranking according to the lowest absolute deviation. Both tables show that there is not one "best" model that outperforms all other models.

With the exception of the RT model, there is always at least one load profile where a model shows better prediction performance than the other models. Considering that, as shown in Figure 1, the absolute deviation is generally low, the coefficient of determination is deemed to be the correct indicator to decide upon the best model for a load profile.

As can be seen in Table 1, it appears that electricity load profiles are best modelled with ARiT or LBNL, sometimes ATR models. The RiT models seem to be the best models to model cooling or heating energy load profiles. The reason for that might be that RiT models are better suited to model weather-dependent consumption while the other models are better suited to model time-dependent consumption.

Table 1: Number of load profiles where each model showed the best prediction performance according to the coefficient of determination (R^2)

type of energy consumption	**number of load profiles where each model on average showed the highest coefficient of determination during the 100 repetitions**				
	ATR	**RT**	**RiT**	**ARiT**	**LBNL**
electricity	16	0	6	68	34
cooling	0	0	13	3	4
heating	0	0	43	0	11

Table 2: Number of load profiles where each model showed the best prediction performance according to the absolute deviation

type of energy consumption	**number of load profiles where each model on average showed the lowest absolute deviation during the 100 repetitions**				
	ATR	**RT**	**RiT**	**ARiT**	**LBNL**
electricity	20	4	21	35	44
cooling	0	1	17	2	0
heating	5	0	28	1	20

Table 3 and 4 give an overview over the prediction performance of the whole airport city when each of the load profiles is modelled by the respective best-performing model. While the average results of the 100 repetitions portray the general magnitude that can be expected, the result of one random repetition illustrates what performance can be expected when the models are trained once and then used in reality.

Considering only the objects that cause 95% of the consumption, the majority of the predictions can be expected to have a R^2 score above 0.7. In case of electricity load profiles, it can be expected that the absolute deviation is below 5%. In case of cooling and heating load profiles, the absolute deviation will most likely be below 10%.

A detailed analysis of the underyling results revealed that the models performed best when a load profile showed a very strong time-dependency and/or weather dependency.

Figure 2 illustrates how well the models' predicted load profiles fit to the corresponding profiles from the test data in three cases: (a) shows a load profile of a building which is strongly interconnected with aeronautical services and thus very dependent from time tables. It can be seen that all five models could predict the profiles very well – the R^2 scores are all above 0.85. (b) is the load profile of a building which is additionally cooled by local fan coils. Therefore, the electricity consumption of this building is dependent from the building's usual usage and it is also dependent from the weather. The prediction performance of the models varies much more – some models can predict the profiles significantly better than other models. (c) shows the load profile of one of the smaller objects, which is not part of the objects that cause 95% of the electricity consumption. The real load profile from the test data appears quite random and thus, the models fail to provide well-fitting predictions.

Table 3: Prediction performances (R^2) achieved in the whole airport city when each of the load profiles is modelled by the model that showed the best prediction performance during the 100 repetitions

coefficient of determination (R^2) of the predicted consumption		average results of 100 repetitions						results of one random repetition					
		all objects			objects that cause 95% of the consumption			all objects			objects that cause 95% of the consumption		
		electricity	cooling	heating	electricity	cooling	heating	electricity	cooling	heating	electricity	cooling	heating
≥ 0.95		2	0	5	1	0	2	1	0	0	1	0	0
≥ 0.9	< 0.95	7	0	12	3	0	8	5	0	16	2	0	10
≥ 0.8	< 0.9	20	11	19	11	7	13	17	3	16	9	3	11
≥ 0.7	< 0.8	22	4	5	12	2	4	31	7	10	13	3	6
≥ 0.6	< 0.7	29	1	6	10	1	3	22	5	4	13	3	2
≥ 0.5	< 0.6	14	3	3	5	3	1	15	2	3	2	2	2
≥ 0.4	< 0.5	9	1	2	3	1	1	6	2	0	2	2	0
≥ 0.3	< 0.4	6	0	2	0	0	0	9	1	1	4	1	1
≥ 0.2	< 0.3	9	0	0	4	0	0	7	0	1	2	0	0
≥ 0.1	< 0.2	4	0	0	0	0	0	7	0	2	1	0	0
	< 0.1	2	0	0	1	0	0	4	0	1	1	0	0

Table 4: Prediction performances (absolute deviation) achieved in the whole airport city when each of the load profiles is modelled by the model that showed the best prediction performance during the 100 repetitions

absolute deviation of the cumulative predicted consumption from the cumulative real consumption		average results of 100 repetitions						results of one random repetition					
		all objects			objects that cause 95% of the consumption			all objects			objects that cause 95% of the consumption		
		electricity	cooling	heating	electricity	cooling	heating	electricity	cooling	heating	electricity	cooling	heating
	≤ 1%	25	0	0	20	0	0	56	3	10	30	2	6
> 1%	≤ 2%	52	0	4	21	0	4	23	1	5	9	1	3
> 2%	≤ 5%	33	12	31	6	10	22	28	3	18	8	2	12
> 5%	≤ 10%	9	6	15	3	3	5	10	10	13	0	8	9
> 10%	≤ 20%	5	2	4	0	1	1	6	3	7	3	1	2
> 20%		0	0	0	0	0	0	1	0	1	0	0	0

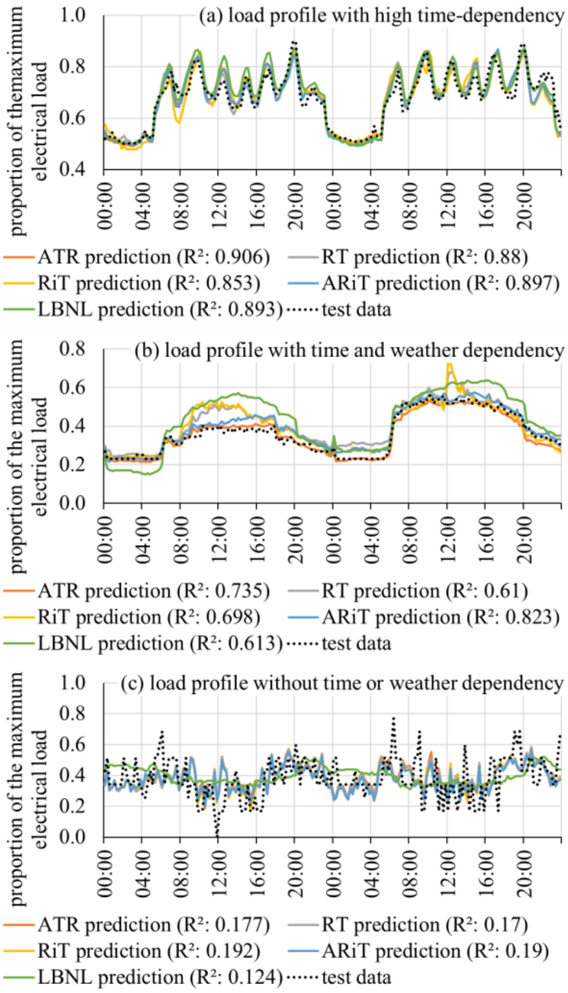

Figure 2: Examples of the models' prediction performance in three different cases

Generally, unique spikes that occurred independent from the time and weather cannot be replicated by the models. Further, structural or operational changes that influence the energy consumption (e.g., office space that is rented or not) can also not be replicated in the presented model configurations. Due to the nature of the underlying synthetically generated load profiles, it is assumed that the models would perform better if they would be trained with the real monitoring data from each object. Nevertheless, the general prediction performance achieved in the whole Vienna airport city is on a level that is deemed good enough for the usage of the models as reference for the nominal energy consumption of each object and energy type.

Conclusion

Multiple linear regression is a useful tool to predict the nominal energy consumption load profiles of buildings and infrastructure. The prerequisite for that is the availability of historical data and ensuring this data contains information about parameters that affect energy consumption – e.g., time-related information or weather data.

Five different models were analyzed. Generally, none of those models is the one best model for all purposes – instead, the decision on the best model had to be done for each load profile. When each of the load profiles is modelled by the respective best-performing model, the predicted energy consumption of the majority of airport city objects can be expected to have an R^2 score above 0.7. The absolute deviation of the cumulative predicted consumption from the cumulative real consumption can be expected to be below 10%.

The presented models and their underlying methods are also applicable to other load profiles from other energy consumers – especially, if they have a strong time- and/or weather dependency. Some of the predictor variables, e.g. the airport-specific "flightplan", will be useless for the modeling of non-airport energy consumers. They should be removed or swapped with other predictor variables.

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