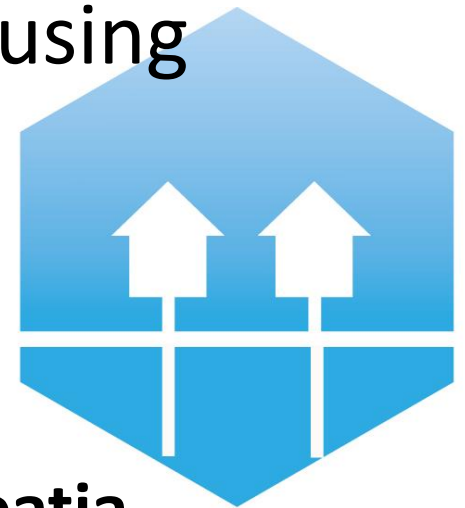


Modelling the impact of installation of heat cost allocators in DH systems using decision tree model



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DENMARK



4DH

**4th Generation District Heating
Technologies and Systems**

Introduction

- EU regulation on energy efficiency, Article 9, introducing mandatory individual metering
- Due to bad communication to the consumers a false perception of HCA was created as devices that save energy by themselves
- Big public disagreement campaign in the press in 2015 in Croatia
- The question – does implementation of HCA result in the energy savings?



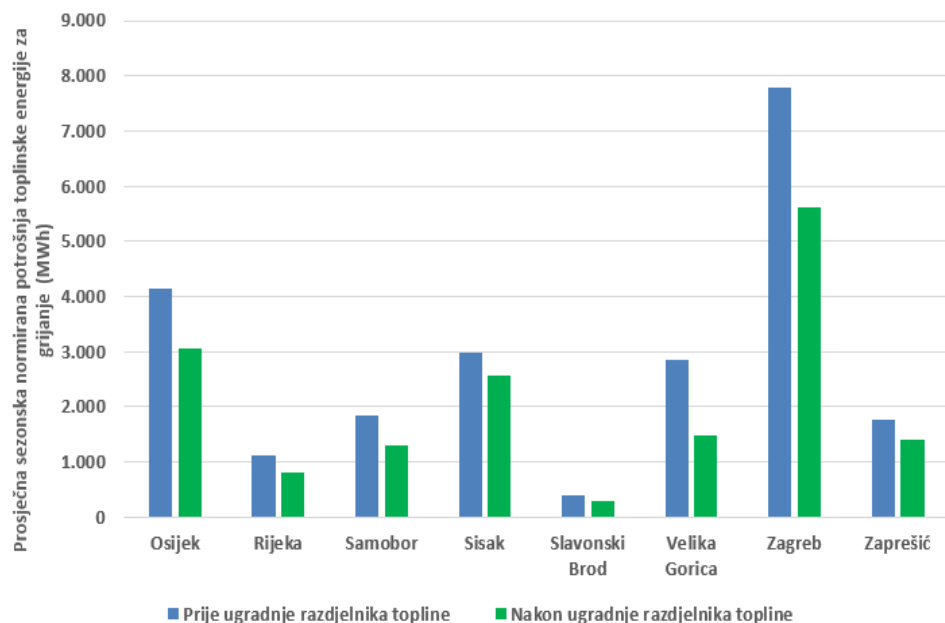
Heat Consumption (in DH)



- Depends on a number of parameters of which some measurable and predictable, while other are hard to predict
- Measurable/predictable:
 - building envelope characteristics
 - heating degree days (climatology)
 - number of occupants
 - schedule of space usage
 - energy source
 - building heat installation losses (including heating substation)
 - position of the apartment in the building
 - formula for calculating consumption in case of HCA
 - *existence of individual metering*
- Hard to predict:
 - heat gains/losses from adjacent apartments
 - heat comfort level in the apartment
 - mode of space usage (opening windows)
 - income level of the owner, readiness to pay



Komparativna analiza učinka ugradnje RTTE za svaki promatrani grad - normirani iznosi



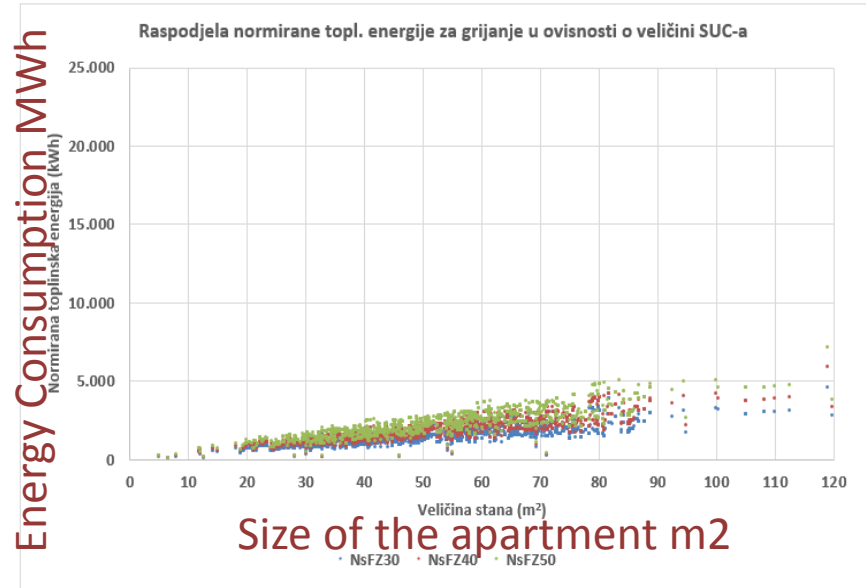
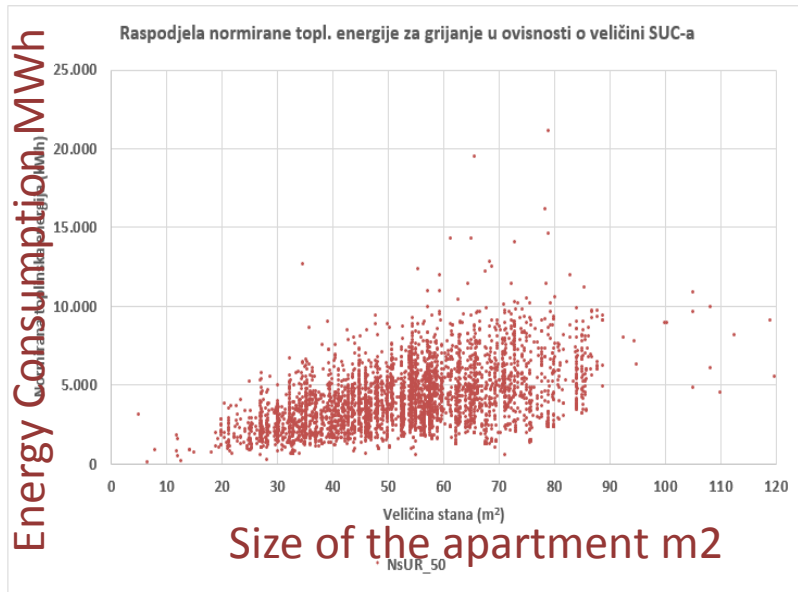
Town	Heat consumption reduction, HDD
Osijek	26,3%
Rijeka	28,3%
Samobor	28,0%
Sisak	14,0%
Slavonski Brod	22,2%
Velika Gorica	48,0%
Zagreb	27,8%
Zaprešić	21,3%



Taking only climatology into account. Savings on the building level.
Are the savings result only of HCA installment?

What happens on the apartment level?

- Adjacent apartments, formula, occupancy and way of usage?



Change in scattering of „consumption” due to the change in the formula. Influences cost.

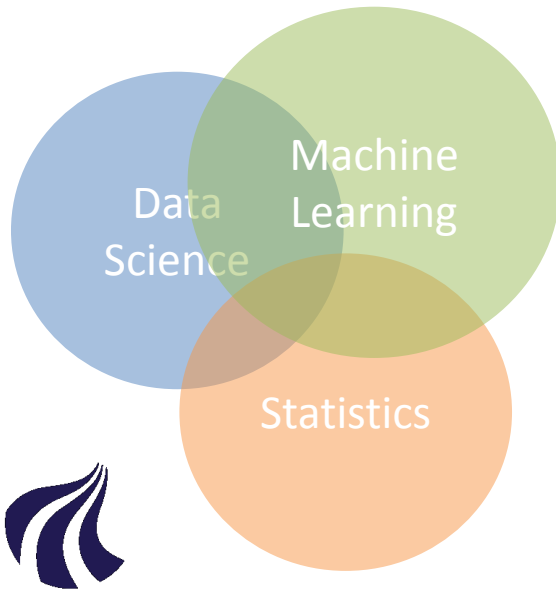


Installation of HCA reduces cost for most, but not all, of the apartments.

Investment in HCA is made by the consumer. How and when is HCA EE measure?

Predicting what is hard to predict

- building energy consumption modelling and the usual methods used are traditional multiple regression models, simulation methods and methods of artificial neural networks
- in the last years machine learning has gain larger application in various fields – „chewing of data”
- gives good results in cases where large amounts of data are to be processed with an aim to recognize a pattern and correlation of each of the relevant parameter as well as in the cases where the problem is too complex for a human intelligence to solve
- decision tree method, has proven an accuracy of over 92% in prediction general building consumption



Interdisciplinary

1. Programming
2. Expertise in the field
3. Mathematics&Statistics

Three steps

1. Data work
2. Choosing of an algorithm
3. Developing a model



6 steps in production

1. Data preparation
2. Data description
3. Learning
4. Evaluation
5. Diagnosis
6. Deployment

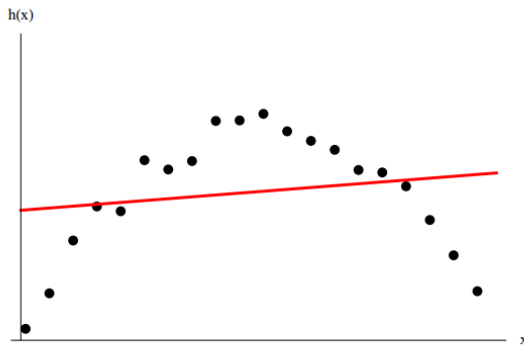


Microsoft Azure

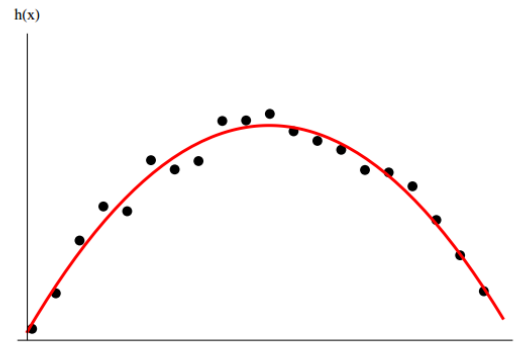


1. Model
2. Error
3. Optimization

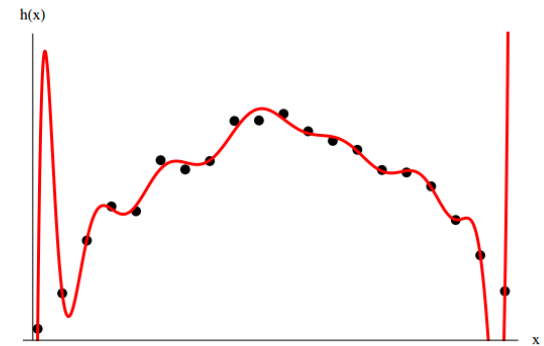
1. Overfitting
2. Underfitting



(a)



(b)

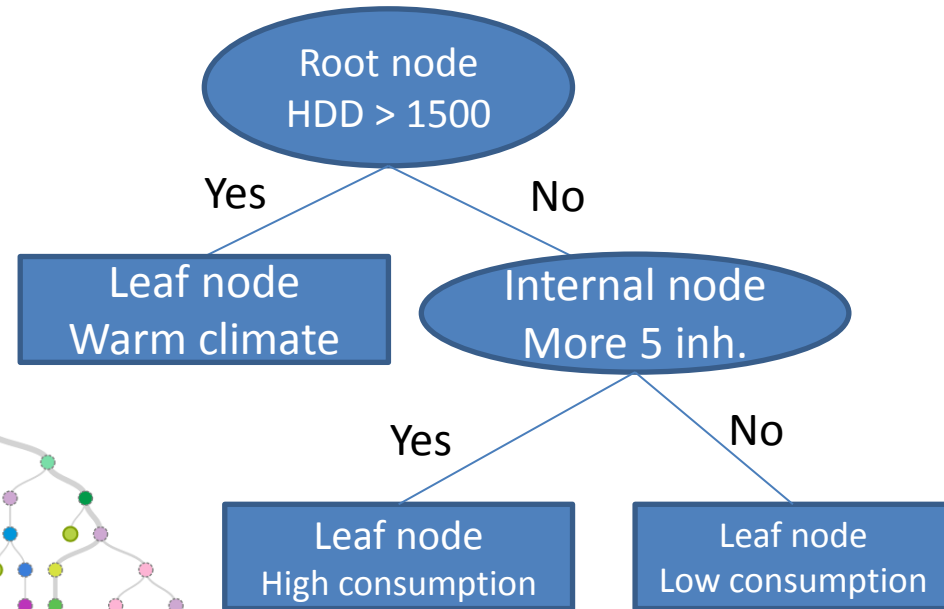


(c)



Decision tree algorithm

Parameter	Type
Building envelope characteristics	Numerical
Heating degree days	Numerical
Number of occupants	Numerical
Schedule of space usage	Categorical
Energy source	Categorical
Building installation losses	Numerical
Position of an apartment	Categorical
Existance of individual metering	Categorical
Confort level in the apartment	Categorical
Rediness to pay	Categorical



Growing a tree

ROOT NODE	1	Node number
	700	Number of data records
	0,9568	Entropy
	HCA installed?	Splitting test
INTERNAL NODE	3	Node number
	200	Number of data records
	0,8500	Entropy
	HDD > 1500	Splitting test
LEAF NODE	10	Node number
	96	Number of data records
	0,0000	Entropy
	E savings	Classification result
	LEAF	Notation if LEAF or STOP



Why this algorithm?

- Popular for decision makers
- Core algorithm is ID3 by J.R. Quinlan (held positions at the University of Sydney, University of Technology Sydney, and RAND Corporation)
- Often it is referred to as a „greedy algorithm” – top-down, never goes back to consider previous node
- Uses Entropy and Information Gain to construct a decision tree
- Top-down from a root node and involves partitioning the data into subsets that contain instances with similar values (homogenous)
- ID3 algorithm uses entropy to calculate the homogeneity of a sample (completely homogenous = 0, sample equally divided = 1)



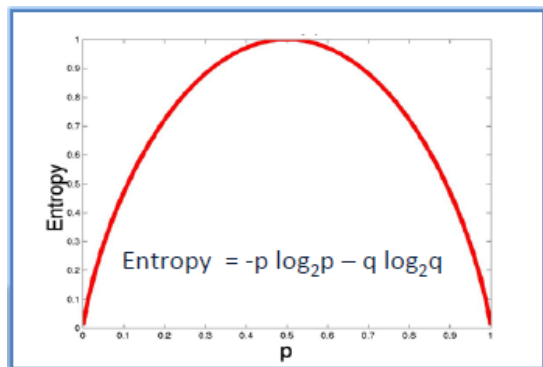
Choose the highest information gain

Have HCA?	
Yes	No
9	5

$$\begin{aligned} \text{Entropy}(\text{HaveHCA}) &= \text{Entropy}(5,9) \\ &= \text{Entropy}(0,36;0,64) \\ &= - (0,36 \log_2 0,36) - (0,64 \log_2 0,64) \\ &= 0,94 \end{aligned}$$

		Have HCA?	
		Yes	No
Schedule of use	<24h	3	2
	<12h	4	0
	<8h	2	3
Gain = 0,250			

$$\begin{aligned} \text{Entropy}(\text{HaveHCA}, \text{Schedule}) &= P(<24h) * \text{Entropy}(3,2) + P(<12h) * \text{Entropy}(4,0) + P(<8h) * \text{Entropy}(2,3) \\ &= (5/14) * 0,971 + (4/14) * 0,0 + (5/14) * 0,971 = 0,693 \end{aligned}$$



		Have HCA?	
		Yes	No
Schedule of use	<24h	3	2
	<12h	4	0
	<8h	2	3
Gain = 0,250			

		Have HCA?	
		Yes	No
Number of occupants	1	2	2
	2	4	2
	>2	3	3
Gain = 0,031			

		Have HCA?	
		Yes	No
HDD	Yes	3	4
	No	6	2
Gain = 0,158			

		Have HCA?	
		Yes	No
Position	Middle	2	6
	Edge	3	3
Gain = 0,051			

$$\text{Gain}(\text{HaveHCA}, X) = \text{Entropy}(\text{HaveHCA}) - \text{Entropy}(\text{HaveHCA}, X)$$

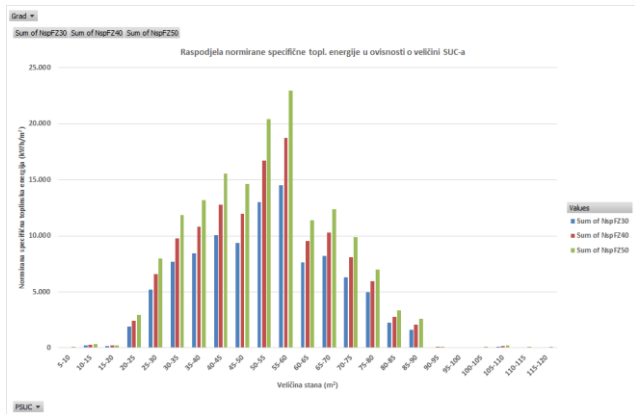
$$\text{Entropy} = -0,5 \log_2 0,5 - 0,5 \log_2 0,5 = 1$$

Choose the attribute with the biggest information gain as a root node. Entropy 0 = leaf node. Entropy >0 needs more splitting – internal node. Run until all data is classified.

Present. Data collection.

Grad	Općina	Ime	Adresa	Tip	Ukupna površina	Ukupna površina	Ukupna površina	Ukupna površina	Ukupna površina	Ukupna površina	Ukupna površina	Ukupna površina	Ukupna površina	Ukupna površina	Ukupna površina	Ukupna površina	Ukupna površina	Ukupna površina	Ukupna površina	Ukupna površina	
Karlovac	20020001	11700	310	4138	1.047.66	1.244.84	1.279.40	1.400.21	1.468.85	1.522.21	1.600.21	1.704.49	24.34	34.13	40.11	28.17					
Karlovac	20020001	11807	305	46	3.091.01	1.540.51	1.246.98	1.105.41	1.773.84	1.239.59	1.501.47	1.763.34	28.34	34.13	40.11	28.17					
Karlovac	20020001	11890	305	44	3.091.01	2.467.05	1.247.21	1.105.41	1.773.84	1.239.59	1.501.47	1.763.34	28.34	34.13	40.11	28.17					
Karlovac	20020001	11891	305	44	3.091.01	2.075.28	1.247.01	1.105.41	1.773.84	1.239.59	1.501.47	1.763.34	28.34	34.13	40.11	28.17					
Karlovac	20020001	11892	305	44	3.091.01	1.930.94	1.247.00	1.105.41	1.773.84	1.239.59	1.501.47	1.763.34	28.34	34.13	40.11	28.17					
Karlovac	20020001	11893	305	44	3.091.01	3.907.34	1.247.17	1.105.41	1.773.84	1.239.59	1.501.47	1.763.34	28.34	34.13	40.11	28.17					
Karlovac	20020001	11894	305	44	3.091.01	2.163.13	1.247.01	1.105.41	1.773.84	1.239.59	1.501.47	1.763.34	28.34	34.13	40.11	28.17					
Karlovac	20020001	11895	305	44	3.091.01	3.111.44	1.247.08	1.105.50	1.773.92	1.239.70	1.501.56	1.763.42	28.34	34.13	40.11	28.17					
Karlovac	20020001	11896	305	44	3.091.01	3.030.31	1.247.14	1.105.79	1.773.91	1.239.70	1.501.56	1.763.42	28.34	34.13	40.11	28.17					
Karlovac	20020001	11897	305	44	3.091.01	4.218.31	1.247.16	1.105.56	1.773.97	1.239.77	1.501.62	1.763.47	28.34	34.13	40.11	28.17					
Karlovac	20020001	11898	305	44	3.091.01	2.076.76	1.247.01	1.105.44	1.773.87	1.239.61	1.501.56	1.763.37	28.34	34.13	40.11	28.17					
Karlovac	20020001	11899	305	44	3.091.01	1.247.17	1.246.98	1.105.41	1.773.84	1.239.59	1.501.47	1.763.34	28.34	34.13	40.11	28.17					
Karlovac	20020001	11877	305	34	3.793.31	1.896.76	1.536.38	1.403.68	2.178.99	1.521.32	1.842.71	2.164.10	28.34	34.13	40.11	28.17					
Karlovac	20020001	11878	305	36	3.934.01	1.795.05	1.407.46	1.402.68	2.257.90	1.576.80	1.911.92	2.244.34	28.34	34.13	40.11	28.17					
Karlovac	20020001	11879	305	36	3.934.01	2.249.42	1.587.88	1.402.35	2.257.61	1.577.68	1.910.97	2.244.38	28.34	34.13	40.11	28.17					
Karlovac	20020001	11881	305	36	3.934.01	4.068.62	1.587.20	1.402.46	2.257.72	1.577.80	1.911.97	2.244.35	28.34	34.13	40.11	28.17					
Karlovac	20020001	11883	305	36	3.934.01	3.921.48	1.587.19	1.402.65	2.257.79	1.577.79	1.911.97	2.244.34	28.34	34.13	40.11	28.17					
Karlovac	20020001	11885	305	36	3.934.01	3.511.61	1.587.19	1.402.41	2.257.69	1.577.76	1.911.94	2.244.32	28.34	34.13	40.11	28.17					
Karlovac	20020001	11886	305	36	3.934.01	2.997.90	1.587.12	1.402.29	2.257.66	1.577.75	1.911.91	2.244.30	28.34	34.13	40.11	28.17					
Karlovac	20020001	11880	305	67	4.706.77	2.364.95	1.898.62	2.296.54	2.761.68	1.867.54	2.286.52	2.465.09	28.34	34.13	40.11	28.17					
Karlovac	20020001	11882	305	67	4.706.77	5.561.45	1.899.02	2.300.12	2.761.23	1.867.77	2.286.51	2.465.14	28.34	34.13	40.11	28.17					
Karlovac	20020001	11884	305	67	4.706.77	3.952.71	1.899.02	2.300.12	2.761.25	1.867.80	2.286.52	2.465.25	28.34	34.13	40.11	28.17					
Karlovac	20020001	11886	305	67	4.706.77	3.997.89	1.898.91	2.300.03	2.761.13	1.867.67	2.286.41	2.465.18	28.34	34.13	40.11	28.17					
Karlovac	20020001	11889	305	67	4.706.77	5.421.18	1.899.02	2.300.11	2.761.22	1.867.76	2.286.50	2.465.21	28.34	34.13	40.11	28.17					
Karlovac	30000001	13483	305	12	820.34	1.548.66	262.53	342.21	461.90	260.97	340.19	478.40	21.88	28.52	35.16	21.79					
Karlovac	30000001	13454	305	36	2.461.02	1.937.94	787.49	1.028.57	1.265.40	782.83	1.028.49	1.258.15	21.87	28.52	35.16	21.79					
Karlovac	30000001	13455	305	36	2.461.02	1.999.83	787.50	1.028.57	1.265.40	782.83	1.028.49	1.258.15	21.87	28.52	35.16	21.79					
Karlovac	30000001	13456	305	36	2.461.02	1.797.34	787.56	1.028.62	1.265.49	782.89	1.028.54	1.258.15	21.88	28.52	35.16	21.79					
Karlovac	30000001	13459	305	36	2.461.02	2.090.53	787.50	1.028.57	1.265.40	782.83	1.028.49	1.258.15	21.87	28.52	35.16	21.79					
Karlovac	30000001	13450	305	36	2.461.02	2.090.53	787.50	1.028.57	1.265.40	782.83	1.028.49	1.258.15	21.87	28.52	35.16	21.79					
Karlovac	30000001	13451	305	36	2.461.02	2.090.53	787.50	1.028.57	1.265.40	782.83	1.028.49	1.258.15	21.87	28.52	35.16	21.79					

- Having data for 50 buildings in mentioned cities (app. 3600 apartments)
- Make questionnaires for the existing building set
- Run ID3 algorithm
- Target – get energy data for all DH in Croatia (end 2016)
- Consider other algorithms – Bayesian Classifier





Thank you for your attention



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