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A Methodology for Quantitative Comparison of Control Solutions with Respect to Cost, Quality and External Conditions

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For each of many systems, devices and processes, the present market offers huge amount of control solutions. Each company claims the savings achieved by their solution are significant. This paper provides a useful methodology for quantitative comparison of the control solutions with respect to operational costs, achieved quality of control and external conditions which could play also an important role. The outputs of this methodology might be helpful in deciding for the most appropriate solution not only for particular system, but also for particular external condition and required quality. Finally, the methodology is demonstrated on the comparison of different HVAC control solutions.

1. Introduction

The comparison of different control solutions applied to the same system is often difficult, because the control solutions are usually not applied under the exactly same conditions. These conditions might have a significant impact on achieved outputs and consumed resources. The requirements on the controlled variables have to be satisfied while the resources have to be minimized. This claim makes the comparison even more difficult: what to do if one control solution c_1 meets the control requirements, but uses more resources while the other control solution c_2 does not meet the requirements fully, but seems to be more economical at the resource consumption. The situation is illustrated in Figure 1.

Employment of statistics for comparison of similar situation is nothing new. Data envelopment analysis – DEA (Charness 1978) calculates the efficiency of each data point with respect to a set of efficient data points. Analysis of variance – ANOVA and related design of experiment approaches (Bailey 2008) examine impact of particular factors on the output and decide the statistical significance of the difference. None of both approaches is suitable for our purposes. DEA assumes the factors have monotonous impact on the outputs, while ANOVA considers only discrete values of factors. The inputs in real systems are frequently continuous and not necessary monotonous.

This paper is organized as follows: Section 2 formulates the problem formally. Then, Section 3 provides proposed methodology. Next, Section 4 demonstrates its application

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in the area of HVAC systems. Finally, Section 5 concludes the paper and proposes future research steps and possible advanced applications.

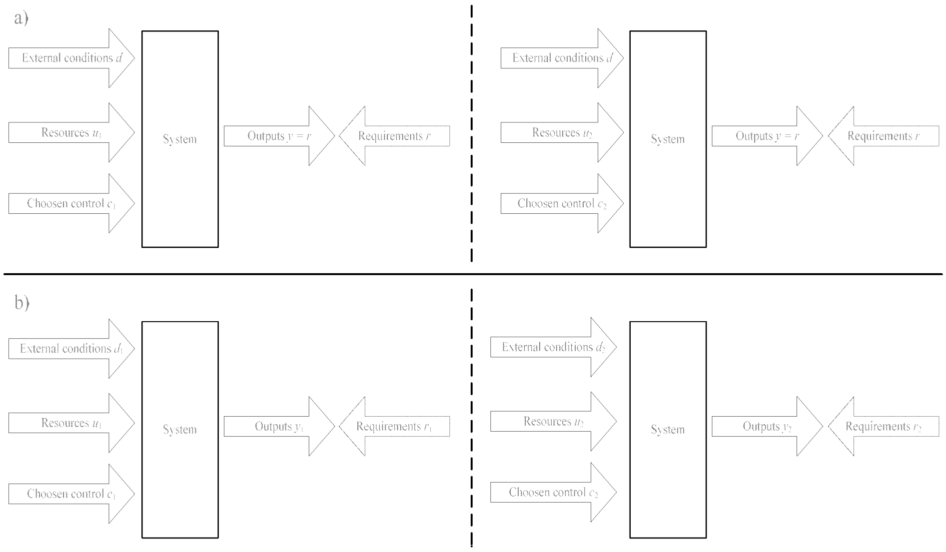

Figure 1: Controls in a) are very easy to be compared: only the costs of used resources are calculated and compared. The situations in b) differ also in external conditions, outputs, and also in requirements. In this case c_1 *and* c_2 *are hard to be compared.*

2. Problem formulation

Let data ($\boldsymbol{d}^{(i)}$, $\boldsymbol{u}^{(i)}$,$c^{(i)}$, $\boldsymbol{y}^{(i)}$, $\boldsymbol{r}^{(i)}$) for i =1, 2, … T be given. The interpretation is obvious from Figure 1 where $\boldsymbol{d}^{(i)}$, $\boldsymbol{u}^{(i)}$, $\boldsymbol{y}^{(i)}$, $\boldsymbol{r}^{(i)}$ are vectors, $\boldsymbol{y}^{(i)}$ and $\boldsymbol{r}^{(i)}$ of the same size. The chosen control solution $c^{(i)}$ is a discrete variable, say from $\{\mathrm{c}_1, \mathrm{c}_2\}$. The problem is to determine the ratio ρ expressing saving by c_2 against c_1. We will split the data set into two subgroups with respect to c: D_1 are data related to c_1 and vice versa D_2 relates to c_2. The data is considered to be collected during time. For the purposes of this work we will use some aggregation for one day where the control solution was fixed. Namely, we will use averaging for d and sum for u. The aggregation of r and y is discussed in more detail bellow. However, this aggregation is generally not necessary.

First, we will calculate ρ for each component of u separately. For this purpose, we consider a random mapping $U|D,Y,R,c$ where U is a random variable now. The ratio can be formulated then as ratio of two expected values:

$$\rho = \frac{\mathrm{E}_{D,Y,R} U \mid D, Y, R, \mathrm{c}_2}{\mathrm{E}_{D,Y,R} U \mid D, Y, R, \mathrm{c}_1} \tag{1}$$

3. Proposed methodology

3.1 Data preprocessing

Because of the system dynamics, it is often useful to aggregate the data for some reasonable time units. E.g. if we compare control solutions in the HVAC systems, one day is a suitable time interval. Most of variables are aggregated by sum (resources, costs). Some characteristics are aggregated by average or median (e.g. outdoor temperature).

3.2 Achieved ratio

The first approximation of ratio ρ from Equation (1) can be calculated as average consumption of resources for given control solution:

$$\rho_{\mathrm{A}} = \frac{1}{|D_2|}\sum_{u_i \in D_2} u_i \bigg/ \frac{1}{|D_1|}\sum_{u_i \in D_1} u_i \tag{2}$$

We will denote ρ_{A} as *achieved* ratio. If the situation is as shown in Figure 1.a, i.e. both control solution work under the same conditions and have the same control performance then ρ_{A} is a suitable approximation of ρ.

3.3 Reference control benchmark and lazy learning

Nevertheless, the impact of external conditions and control performance cannot be omitted in general case. For this purpose, we introduce the *reference* control solution baseline, i.e. a mapping $u^*(r,y,d)$. Since, the reference behavior is usually not available explicitly, it is necessary to use the data to construct it. We can consider following baselines:

- *Original control* - the baseline is constructed from data for one strategy, say D_1. In this case the savings for the other strategy can be calculated directly. However, if the control solutions work under significantly different conditions, the benchmarking model faces problems with extrapolations to domain of D_2.

- *Ideal control* – from the data, only so called non-dominated measurements are selected, both from D_1 and D_2. This approach is motivated similarly as the DEA methodology. However, our early experiments have shown this approach is very sensible to outliers and requires proper robustness analysis. If all factors are taken into account, the ideal baseline can really express the efficiency as such.

- *Average control* – in this case, all data are taken. This approach is very robust and respects the fact that both strategies work under significantly different conditions. It is not necessary to specify which factors have positive and which negative impact on the resources consumed.

Since we intend to propose methodology comparison methodology as generic as possible, we have chosen well known local regression which follows lazy learning principle (Cleveland 1979).

Lazy learning is suitable for modeling nontrivial functions. However, it tends to be poor at extrapolation (Wasserman 2006). Therefore, the average control baseline has been chosen while the ideal and original controls were omitted. Also this was the reason, why we did not fit the data twice, for each control and then put them into the Equation (1).

Now, we can use lazy learning for estimation of consumed resources u, i.e. given the data ($d^{(i)}$, $u^{(i)}$, $y^{(i)}$, $r^{(i)}$) for i =1, 2, … T, we obtain $u^{*\,(i)} = u^{*\,(i)}$ ($d^{(i)}$, $y^{(i)}$, $r^{(i)}$)). The used control solutions were not considered and distinguished here. Hence, the $u^{*(i)}$ means the reference value. Let us consider following ratio:

$$\rho_{\mathrm{E}} = \frac{1}{|D_2|} \sum_{(r_i,y_i,d_i)\in D_2} u^*(r_i, y_i, d_i) \Bigg/ \frac{1}{|D_1|} \sum_{(r_i,y_i,d_i)\in D_1} u^*(r_i, y_i, d_i) \qquad (3)$$

This number expresses the expected ratio between resources in c_2 and c_1 days if the baseline control would be applied. Using ρ_{A} and ρ_{E}, we can estimate control performance ratio as $\rho \approx \rho_{\mathrm{A}}/\ \rho_{\mathrm{E}}$.

The approximate sign $\approx$ can be read as conservative estimate: if the data for c_1 and c_2 do not overlap sufficiently, they are considered as similar, i.e. $\rho \approx 1$. If the data overlap sufficiently, the estimate is close $\rho = \rho_{\mathrm{A}}/\ \rho_{\mathrm{E}}$. Precise assessment of these results requires a detailed analysis in terms of probability theory and mathematical statistics.

3.4 Distinguishing scheduling and resource savings

We have already demonstrated how the savings of resources can be evaluated. For each resource i, we have ρ_i expressing the ratio of expected consumptions for c_1 and c_2. All the resources are related to some costs. In order to compare the c_1 and c_2, we can take the costs as an input u for previous analyses. We obtain ρ_{costs} for costs which corresponds to the overall savings.

However, the prices of resources might vary during one day. The control solution may take into account this fact and operate the system more intensively when the prices are low. It is helpful to be able to identify this situation. In case of one resource, we could simply divide the overall savings by the resource savings. If more than one resource is consumed, the situation is more difficult. We have to introduce an overall resource saving ratio ρ_{res}. For this ratio, we will consider relative costs α_i of resources that are proportional to overall costs for particular resources and $\Sigma\alpha_i = 1$.

$$\rho_{\mathrm{scheduling}} = \rho_{\mathrm{costs}} / \rho_{\mathrm{res}} = \rho_{\mathrm{costs}} \Bigg/ \left(\sum_{\mathrm{i}=1}^{N_r} \alpha_i \rho_{\mathrm{i}} \right) \qquad (4)$$

3.5 Involving long term changes of the prices

Another aspect with the pricing relates to long term changes. Considering fixed prices which might change, but their ratio is remains the same, the situation is easy: we simply recalculate costs for older data so the results are comparable. However, at least the ratio might change, i.e. gas can become relatively cheaper than electricity. In this case, the prices or the ratio can be taken into account as a variable (part of vector d) of above discussed local regression model so the information is involved.

3.6 Dealing with constraints

Sometimes, the constraints on the system outputs have to be considered explicitly. For the evaluation, it is possible to assign to given combination of r and y a utility value and use it in Equation (3) instead of r and x. Alternatively, the data can be divided into classes with different levels of constraint dissatisfaction and compare the savings only under peers. The output of the analysis would be a multi-criteria comparison. Then, only the users can decide which control seems to be more suitable for them.

4. Case study: HVAC Supervisory Control

The goal is to compare two supervisory control strategies used for control of HVAC equipment in an administrative building. Generally, the primary goal of any control strategy is to keep defined comfort in all building zones and secondary objective is to do it cost-effective minimizing purchased energy costs. Compared control strategies use same HVAC equipments and same building. The difference in strategies is in setting of important HVAC set-points (e.g. supply air temperature, supply hot water temperature, supply fan speed, etc.).

First strategy c_1 is the original HVAC control with static set-points and few rule-based methods as ambient temperature compensation of heating and cooling water temperature. Second control strategy c_2 is tested novel control strategy based on model-based optimization approach. Both strategies cannot run simultaneously as we have just one controlled system (building) in our case. Though testing site offered twin-building we didn't adopt "parallel-run" approach as in Prívara (2011) for there was difference in twin-buildings occupancy profiles. Thus, strategies are changing on day-by-day basis in order to allow performance comparison.

There are two performance measures associated with HVAC control strategy – (i) comfort satisfaction and (ii) operating costs. In our case, the first measure may be omitted for both compared strategies are pretty conservative and don't compromise defined comfort. We should consider different operating conditions. In case of HVAC control strategies the considered conditions are (i) occupancy and (ii) weather. It is reasonable to omit occupancy information in our case as our system is an administrative building. There are three reasons for it: (1) performance is compared just for working days (HVAC is off during holidays); (2) the building is large and an expected variance in occupancy is small; (3) occupancy information is not available/measured.

Regarding the weather condition, the most influencing factor for energy consumption is ambient temperature. Daily average aggregate was chosen as conditional variable.

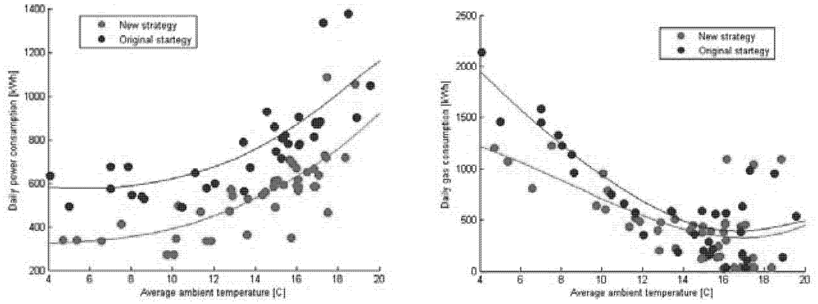

Figure 2: Daily power and gas consumptions conditioned by average ambient temperature. Lines are results of local regression (LOESS) smoothing using linear temperature-consumption model and Gaussian ($\sigma = 3$ K) kernel.

Table 1: Results from the case study

		Gas	*Electricity*	*Total*
Achieved savings	$1-\rho_A$	0.3149	0.2767	0.2869
Savings by new control	$1-\rho$	0.1948	0.2869	0.2636

Note the difference between savings derived from simple average ratio ρ_A and savings corrected to real ambient conditions ρ. Correction is significantly negative for gas and slightly positive for electricity.

5. Conclusion

Presented methodology offers comparison of two or multiple control strategies even in case operating conditions are not same. Comparison is conservative: for significantly different (non-overlapping) operating conditions control strategy are rated as equivalent. When operating conditions overlaps then estimated savings are close to savings evaluated by simple averaging.
This methodology can be used not only for the comparison as such, it can be also applied as a driver for automated switching between different control solutions so the best for given conditions and requirements is selected.

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