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Modeling and prediction for optimal Human Resources Management

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Abstract: Human resources management is key for the retention and development of quality staff in modern companies. With the advent of big data and the recent boost in computing power, modeling and predictive analytics have shown their potential to increase HR-related performance, thus making the companies more competitive on the market via data-driven solutions. In this work, we develop a predictive model of the annual hourly cost per employee in big maintenance companies, which is usable for sales, marketing and HR purposes. With experimental real data, we show that such a model outperforms the typically employed solutions, by also allowing for an adaptive implementation using monthly updates.

Keywords: statistical analysis, big data, economics

1. INTRODUCTION

In modern companies, the purpose of human resources management (HRM) is typically three-fold: to measure the employee performance and engagement, to study the workforce collaboration patterns and to analyze the employee churn and turnover to model the employee lifetime value, Mishra et al. (2016). The final goal is to keep HR-related costs low, while optimizing the business performance as well as the employee engagement and satisfaction, Noe et al. (2017); Stewart and Brown (2019).

With the recent boost in computing power and its affordability and being big data digitally accessible via cloud storage for processing, modeling and analytics tools have become key to approach the increasingly competitive market with rapid business (including HR-related) data-driven solutions, see, e.g., Strohmeier and Piazza (2013); Das (2013); Akerkar (2013). Electronic HRM systems (e-HRMs) are then now a reality at the intersection of information systems and HRM science and are more and more studied also within the academic environment, see, e.g., Thite (2019); Bondarouk and Ruël (2009); Lin (2011). An effective control theoretic approach to HRM, as originally conceived and suggested in Snell (1992) more than 25 years ago, can be made possible now, thanks to data-driven models and prediction analytics. A couple of examples within the IFAC world are, e.g., Harzallah and Vernadat (1999); En-nahli et al. (2015).

In this work, we address a specific problem in HR (so far never addressed with control theoretic modeling tools), that is the prediction of the annual hourly average cost per employee for a general personnel in big maintenance companies. In particular, we derive a predictive model based on the cost laws to be used in the budgeting phase. Such a model may provide interesting indications for strategic decisions and possible preventive actions to undertake in personnel management. Formally, given a generic site, the annual average hourly cost for a general year x, subsequently indicated as c_{m_x}, can be defined as the ratio between the total costs c_{tot_x} and the overall effective working hours h_{eff_x} in year x:

$$c_{m_x} = \frac{c_{tot_x}}{h_{eff_x}} \tag{1}$$

Then, the above described objective can be formalized as the attainment of a predictive model that provides an estimate for the annual hourly average cost per employee, following denoted as $\hat{c}_{m_x}$, such that the prediction error is, in absolute value, lower than an a-priori specified threshold value ϵ, i.e.,

$$|\hat{c}_{m_x} - c_{m_x}| < \epsilon. \tag{2}$$

To assess the prediction performance of the proposed modeling approach, we compare it using real data provided by a Facility Management leading company with the three benchmark solutions typically employed in the HRM practice:

- *Benchmark Solution 1:* the average annual hourly cost for the year x is assumed to be equal to the average annual hourly cost for the year $x-1$;
- *Benchmark Solution 2:* the average annual hourly cost for the year x is computed as the mean of the annual hourly costs for the past n years;
- *Benchmark Solution 3:* working hours and costs of the year $x-1$ are linearly projected over the year x under the hypothesis of partial knowledge of year x.

The experimental analysis will show that the proposed model-based approach to prediction (where all the phenomena of interest are taken into account and few mild assumptions are needed) generally outperforms the classical solutions. Moreover, an adaptive implementation using incoming monthly data is allowed, which is most suited for the modern rapidly changing markets.

The remainder of the paper is as follows. The predictive model for the estimate of the annual average hourly cost is derived in Section 2. The adaptive version of the proposed predictive algorithm is provided in Section 3. The prediction performance assessed on experimental data taken from real sites is illustrated in Section 4. The paper is ended by some concluding remarks.

2. THE PROPOSED PREDICTIVE MODEL

The most common solutions for the estimation of the annual average hourly cost for a generic year x rely on the projection of the available information related to past years on the site of interest. A *trivial* strategy may consist in simply assuming that the annual average cost for the year x is equal to the one computed for the previous year:

$$\hat{c}_{m_x} = c_{m_{x-1}} \tag{3}$$

Despite of a very low complexity, this solution is highly conditioned by anomalies characterizing a specific year, that are blindly re-projected over the subsequent year. Moreover, this strategy does not take into account any prior information about year x that could be potentially available at the estimation moment. As a matter of fact, information about, for instance, the number of working and holiday days (that strictly depend on calendar) or possible contractual variations are usually known in advance and may be included in the estimation procedure.

A slight variant imposes the average annual hourly cost for the year x equal to the mean value of the average annual hourly costs for the past n years. This strategy allows to average the effect of isolated anomalies related to specific years, but still presents the other drawbacks previously described. Moreover, it requires the availability of possibly large historical datasets, that for newly formed or highly dynamical sites could represent a critical hypothesis.

More sophisticated *prediction-oriented* strategies are based, instead, on the derivation of very accurate models for the projection of past data over year x. The main drawback related to this kind of approaches is that they generally rely on the knowledge assumption of critical parameters at the estimation moment, commonly the number of employees for year x.

Our proposed solution follows a *prediction-oriented* approach, but the derived model *does not require the prior knowledge of critical parameters about year x*. Indeed, the estimation of the annual average hourly cost only depends on data related to the previous year with the inclusion of a-priori information associated to year x that are surely known, such as the number of working and holiday days, possible contractual variations or health care costs.

In the next subsections, the model for the projection of costs and hours contributions in (1) will be further detailed.

2.1 Working hours

This section explains the computation strategy for the total effective working hours for a generic year x, through the projection of information related to the year $x - 1$. Although the derivation of each single contribution related to hours may depend on the number of employees n_{empl_x} at year x, that generally represents an unknown parameter at the estimation moment, at the end of the dissertation the independence of the estimate from the number of employees will be proved.

For a generic site, the number of total effective working hours h_{eff_x} in year x depends on the theoretical potentially available working hours h_{theor_x} according to the calendar of year x. Then, starting from this contribution, it is necessary to subtract the number of absence hours h_{abs_x} and to add the number of additional presence hours, possibly split into over-time hours h_{over_x} and extra-time hours h_{extra_x}. This latter classification is mainly a technical characterization that will reflect into a different cost computation through the application of the corresponding rate for each term.

The number of total effective working hours can be then expressed as:

$$h_{eff_x} = h_{theor_x} - h_{abs_x} + h_{over_x} + h_{extra_x} \tag{4}$$

The number of theoretical working hours is given by the difference between potential working hours h_{work_x} and holiday hours h_{hol_x} in accordance with calendar, projected over the part-time percentage $PT_{\%_x}$ for each employee and finally scaled over the number of employees n_{empl_x}:

$$h_{theor_x} = (h_{work_x} - h_{hol_x}) \cdot PT_{\%_x} \cdot n_{empl_x} \tag{5}$$

It is, here, assumed that the part-time percentage for each employee is established during contract stipulation and, accordingly, it represents a known parameter at the estimation moment.

Concerning the computation of absence and additional hours for year x, a *prediction-oriented* approach will be adopted to project the percentage of each contribution with respect to the theoretical hours computed for the year $x-1$ over the number of theoretical hours derived for year x in (5):

$$h_{abs_x} = \frac{h_{abs_{x-1}}}{h_{theor_{x-1}}} \cdot h_{theor_x} \tag{6}$$

$$h_{over_x} = \frac{h_{over_{x-1}}}{h_{theor_{x-1}}} \cdot h_{theor_x} \tag{7}$$

$$h_{extra_x} = \frac{h_{extra_{x-1}}}{h_{theor_{x-1}}} \cdot h_{theor_x} \tag{8}$$

By combining (5), (6), (7) and (8), an expression for h_{eff_x} is finally derived as a function of past year data and certainly known parameters related to year x.

2.2 Fixed and Variable Costs

Total costs for a generic site can be usually classified into *fixed costs*, c_{fix_x}, and *variable costs*, c_{var_x}, and these two macro-categories generally include several contributions. Highlighting the described cost characterization, the annual hourly cost for year x can be then expressed as:

$$c_{m_x} = \frac{c_{fix_x} + c_{var_x}}{h_{eff_x}} \tag{9}$$

Fixed costs are mainly related to liquidated salary, health care insurance and fixed contribution fees; the projection strategy for each fixed cost item $c_{fix_{x,i}}$ consists in the projection of the percentage of each contribution with respect to the effective hours computed for the year $x-1$ over the number of effective hours derived in (4):

$$c_{fix_{x,i}} = \frac{c_{fix_{x-1,i}}}{h_{eff_{x-1}}} \cdot h_{eff_x} \tag{10}$$

Variable costs are, contrariwise, mostly associated to more *unpredictable* phenomena, such as additional hours, absence, injuries, maternity hours and variable contribution fees. The prediction approach is similar to the one described for fixed costs but the projection related to each contribution $c_{var_{x,i}}$ happens on the theoretical hours instead of the effective hours:

$$c_{var_{x,i}} = \frac{c_{var_{x-1,i}}}{h_{theor_{x-1}}} \cdot h_{theor_x} \tag{11}$$

Regarding contribution fees, over and extra time costs, the proposed approach introduces a modification with respect to the trivial projection over working hours to improve estimation performances. For each mentioned contribution, it is possible to assume that the respective rate for year x is known because usually established by national agreements and can be used for prediction purposes. More in detail, the projection for contribution fee will be performed also over the respective rate $\%_{contr}$:

$$c_{contr_x} = c_{contr_{x-1}} \cdot \frac{h_{theor_x}}{h_{theor_{x-1}}} \cdot \frac{\%_{contr_x}}{\%_{contr_{x-1}}} \tag{12}$$

A similar approach is adopted for over-time and extra-time costs using the related rates, respectively $\%_{over_x}$ and $\%_{extra_x}$, that represent the actual distinctive feature between the two contributions:

$$c_{over_x} = c_{over_{x-1}} \cdot \frac{h_{theor_x}}{h_{theor_{x-1}}} \cdot \frac{\%_{over_x}}{\%_{over_{x-1}}} \tag{13}$$

$$c_{extra_x} = c_{extra_{x-1}} \cdot \frac{h_{theor_x}}{h_{theor_{x-1}}} \cdot \frac{\%_{extra_x}}{\%_{extra_{x-1}}} \tag{14}$$

The total fixed and variable costs expressions, respectively c_{fix_x} and c_{var_x}, will be obtained by summing up the projections related to each fixed and variable contribution.

2.3 Additional a-priori information available on year x

A relevant innovative aspect introduced by the proposed strategy regards the inclusion of additional a-priori information about year x that are available at the estimation moment. This information is related to contractual aspects established at national level and, consequently, perfectly known with a reasonable advance. In detail, it is assumed to know the annual health care insurance cost per employee c_{hc}, the annual guaranteed contractual minimum per employee c_{mc} and the increase in monthly salary for long service bonus ls. In a prediction perspective from year $x-1$ to year x, each contribution reflects into a differential cost, respectively Δ_{hc_x}, $\Delta_{ctr\ var_x}$ and Δ_{ls_x}, whose explicit expressions are further derived:

$$\Delta_{hc_x} = \left(c_{hc_x} - c_{hc_{x-1}}\right) \cdot n_{empl_x} \tag{15}$$

$$\Delta_{ctr\ var_x} = \left(c_{mc_x} - c_{mc_{x-1}}\right) \cdot PT_{\%_x} \cdot n_{empl_x} \tag{16}$$

$$\Delta_{ls_x} = ls_x \cdot 12 \cdot PT_{\%_x} \cdot n_{empl_x} \tag{17}$$

The additional a-priori information are translated into variations of the fixed and variable costs estimates with respect to the simple projection of past year data:

$$c_{fix_x} = \sum_i c_{fix_{x,i}} + \Delta_{c_{fix_x}} \tag{18}$$

$$c_{var_x} = \sum_i c_{var_{x,i}} + \Delta_{c_{var_x}} \tag{19}$$

The term $\Delta_{c_{fix_x}}$ includes the differential effect due to the cost variation introduced by the additional information over each fixed cost contribution. As an example, considering the *13th-month bonus*, that represents a fixed cost contribution whose value is equal to the monthly salary, the respective cost variation term $\Delta_{cost_{13th}}$ can be defined as:

$$\Delta_{cost_{13th_x}} = \frac{\Delta_{ctr\ var_x} + \Delta_{ls_x}}{12} \tag{20}$$

Following a similar reasoning, it is possible to evaluate the impact of variable cost variations on $\Delta_{c_{var_x}}$. More in detail, part of these variation contributions is related to absence hour costs:

$$\Delta_{cost\ abs_x} = \frac{\Delta_{ctr\ var_x} + \Delta_{ls_x}}{h_{theor_x}} \cdot h^*_{abs_x} \tag{21}$$

where $h^*_{abs_x}$ indicates the absence hours after deducting overdue vacation time and absence hours paid by company.

Further relevant terms concern over-time and extra-time costs, whose respective cost variations are computed as:

$$\Delta_{ot_x} = \left(\frac{\Delta_{ctr\ var_x} + \Delta_{ls_x}}{h_{theor_x}} + \frac{\Delta_{ctr\ var_x}}{h_{theor_x}} \cdot \%_{over_x}\right) \cdot h_{over_x} \tag{22}$$

$$\Delta_{et_x} = \left(\frac{\Delta_{ctr\ var_x} + \Delta_{ls_x}}{h_{theor_x}} + \frac{\Delta_{ctr\ var_x}}{h_{theor_x}} \cdot \%_{extra_x}\right) \cdot h_{extra_x} \tag{23}$$

Finally, the effect of differential cost introduction on variable contribution fee cost calculation can be expressed as:

$$\Delta_{contr_x} = \left(\Delta_{cost\ abs_x} + \Delta_{ot_x} + \Delta_{et_x}\right) \cdot \%_{contr_x} \tag{24}$$

The variable costs variation can be, eventually, derived:

$$\Delta_{c_{var_x}} = \Delta_{cost\ abs_x} + \Delta_{ot_x} + \Delta_{et_x} + \Delta_{contr_x}. \tag{25}$$

2.4 Overall Predictive Model derivation

Combining all the derived expressions to obtain the overall predictive model, it can be easily proved that both the numerator and denominator in (1) factorizes with respect to the number of employees at year x, that accordingly simplifies. This demonstrates the independence of annual hourly average cost from n_{empl_x}, that makes the estimate only dependent on past year data and known parameters related to year x at the estimation moment.

3. THE ADAPTIVE IMPLEMENTATION

The predictive model derived in the previous section represents a powerful tool in budgeting phase to provide the hourly cost estimation for a generic year x based only on the past available information related to the preceding year. Anyway, as time progresses, it can be assumed that new consumptive data are available at the end of each month for year x and this information can be used to progressively update the initial annual estimation and to make it converge to the real annual hourly cost. This introduces the need of an adaptation strategy to include monthly consumption information for the initial estimation update. Firstly, it must be noticed that the annual average cost estimation is different from the mean value of the monthly cost estimations:

$$\hat{c}_{m_x} = \frac{\widehat{\sum_{i=1}^{12} c_{tot_i}}}{\widehat{\sum_{i=1}^{12} h_{eff_i}}} \neq \frac{1}{12}\sum_{i=1}^{12}\frac{\widehat{c}_{tot_i}}{\widehat{h}_{eff_i}} \tag{26}$$

and, accordingly, it is not possible to individually replace each monthly estimation with the respective consumptive cost computed at the end of the month. Moreover, if total cost and hours estimates are considered separately, it is possible to show that:

$$\hat{c}_{m_x} = \frac{\widehat{\sum_{i=1}^{12} c_{tot_i}}}{\widehat{\sum_{i=1}^{12} h_{eff_i}}} \neq \frac{\sum_{i=1}^{12}\widehat{c}_{tot_i}}{\sum_{i=1}^{12}\widehat{h}_{eff_i}} = \frac{\widehat{c}_{tot_1} + ... + \widehat{c}_{tot_{12}}}{\widehat{h}_{eff_1} + ... + \widehat{h}_{eff_{12}}} \tag{27}$$

so that single cost or hours estimates cannot be substituted by the respective consumptive value computed at the end of each month.

For these reasons, a more articulated adaptation logic must be introduced. First of all, at the end of each month the overall *'consumptive'* and *'estimation'* periods are identified; more in detail, at the end of a generic month n, the *'consumptive period'* will include months from 1 to n, while the *'estimation period'* will include months from $n+1$ to 12. Then, the total cost and working hours for the overall consumptive period and estimation period are computed separately. Furthermore, with the aim of improving estimation performances, weights, respectively w_{cons} and w_{est}, are introduced to weight the two distinct periods with respect to the effective monthly working days.

The resulting estimate has the following form:

$$\hat{c}_{m_x} = \frac{w_{cons}\cdot\sum_{i=1}^{n} c_{tot_i} + w_{est}\cdot\widehat{\sum_{i=n+1}^{12} c_{tot_i}}}{w_{cons}\cdot\sum_{i=1}^{n} h_{eff_i} + w_{est}\cdot\widehat{\sum_{i=n+1}^{12} h_{eff_i}}} \tag{28}$$

where

$$w_{cons} = \frac{\sum_{i=1}^{n} d_i}{d_{tot_x}} \quad , \quad w_{est} = \frac{\sum_{i=n+1}^{12} d_i}{d_{tot_x}} \tag{29}$$

and d_i represents the number of effective working days for month i, while d_{tot_x} the total number of working days in year x.

The proof of convergence of the proposed estimate to the real average annual cost for $n = 12$, and so at the end of the year x, is trivial and is here omitted for brevity.

4. EXPERIMENTAL RESULTS

4.1 Detailed assessment on an Italian hospital site

Predictive model performances have been firstly evaluated on an hospital site located in an Italian city; for confidentiality reasons, in the following it will be denoted as *City* 1. The considered site is characterized by a division of employees in 3 levels, numbered in increasing order according to the corresponding degree of specialization. The available historical data-set includes the detailed working hour and cost information for each employee with monthly resolution, split into the relevant contributions, in the time interval from January 2013 to December 2016. The average number of employees for each level in the analyzed period is summarized in Table 1.

	Level 1	**Level 2**	**Level 3**
Avg No. Employees	20	270	75

Table 1. Average Number of Employees

Predictive model performances are evaluated in terms of prediction error for the annual average hourly cost estimate per employee, for each level of specialization. The target threshold value defining prediction error bound is defined as:

$$|\hat{c}_{m_x} - c_{m_x}| \leq 0.20 \text{ €} \tag{30}$$

that represents about the 1% of the consumptive annual average hourly cost estimate for each level.

	Level 1	**Level 2**	**Level 3**
Proposed Solution	0.031	0.151	0.007
Benchmark Solution 1	0.051	−0.125	−0.148
Benchmark Solution 2	0.051	−0.125	−0.148
Benchmark Solution 3	−0.938	0.208	0.257

Table 2. Annual Average Hourly Cost Prediction Error [€] - 2014

	Level 1	**Level 2**	**Level 3**
Proposed Solution	−0.401	−0.177	0.034
Benchmark Solution 1	−0.461	−0.288	−0.033
Benchmark Solution 2	−0.335	−0.201	−0.041
Benchmark Solution 3	−2.987	−0.204	0.412

Table 3. Annual Average Hourly Cost Prediction Error [€] - 2015

	Level 1	**Level 2**	**Level 3**
Proposed Solution	0.052	0.181	0.075
Benchmark Solution 1	0.135	0.266	0.165
Benchmark Solution 2	−0.187	−0.032	0.038
Benchmark Solution 3	0.452	0.460	0.558

Table 4. Annual Average Hourly Cost Prediction Error [€] - 2016

According to the available historical data and the predictive projection strategy, prediction errors are evaluated in the period from 2014 to 2016. Prediction errors returned by the proposed solution are, then, compared with the ones obtained by the application of the benchmark strategies mentioned in *Section 1*. Finally, annual average prediction errors, weighted on the number of total effective working hours per level of employees, are computed for the proposed strategy in the considered years, as reported in Table 5.

	Weighted Average Prediction Error
2014	0.112
2015	−0.136
2016	0.149

Table 5. Annual Weighted Average Hourly Cost Prediction Error [€]

From the previous tables, it can be observed that when the proposed model is applied, the prediction error always lies between the specified bounds for all the levels in the considered time interval. The only exception regards Level 1 in 2015 but, related to this case, it has been observed a-posteriori that an anomaly trend in absence hours affected the level. Furthermore, the numerousness of Level 1 is definitely lower if compared with the other two levels and, then, the impact of the corresponding prediction error on the overall error for the site is quite negligible. It can also be noticed that, in most cases, benchmark strategies return prediction error values that overshoot bounds. Concerning weighted average prediction error, instead, it respects the threshold conditions in all the three years for the considered site.

4.2 Validation on 3 other case studies

Predictive model has been, then, validated on 3 further sites located in several Italian geographic areas and with different average number of employees and levels of specialization with respect to *City* 1 site on which model performances have been previously tested. For the same confidentiality reasons, the cities will be further indicated as *City* 2, *City* 3 and *City* 4. The main features related to the new sites are summarized in Table 6.

	Employees Avg Nr.	Levels
City 1 Site	365	3
City 2 Site	285	5
City 3 Site	185	5
City 4 Site	210	6

Table 6. Validation Sites Characteristics

The adopted performance index for model validation is, as already previously discussed, the prediction error for the annual average hourly cost estimate per employee. With a view to a fair comparison with the results obtained for *City* 1 site, because of the different structural level subdivision and average annual number of employees for the new sites, weighted prediction errors have been considered in the same time interval $2014 - 2016$.

From Table 7, it is possible to observe that the weighted average prediction error for each new site is at most equal to 0.20 €. Since these results are compliant with the requirement on prediction error desired bound, predictive model can be considered as validated on the new sites.

	City 2 Site	City 3 Site	City 4 Site
2014	0.074	0.041	0.019
2015	0.193	0.073	0.200
2016	0.162	0.050	0.179

Table 7. Weighted Average Prediction Error [€]

4.3 Monthly Online Adaptation

The monthly online adaptation strategy has been applied to the *City* 1 site in the same time interval from 2014 to 2016. For the sake of space, we do not report here the results on the other sites, but we remark that the conclusions are qualitatively the same. In Figure 1, the prediction error monthly trend is shown for each level of employees in 2015 and compared to the desired bounds of ± 0.20 €. It can be observed that prediction errors always lies between the defined thresholds, apart from the first 5 months for level 1 mainly due to the intrinsic variability of the level. Moreover, as expected, the prediction error converges to 0 for each level at the end of the year.

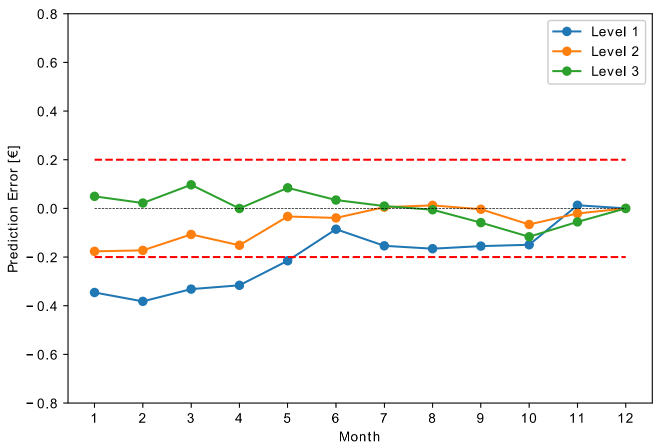

Fig. 1. Prediction Error; Monthly Trend per level

Finally, for the analyzed years, the monthly prediction error weighted with respect to the effective working hours is shown in Figure 2, denoting that the monthly weighted prediction error always lie between the thresholds.

5. CONCLUDING REMARKS

In this work, the HR-related problem of predicting the annual hourly cost per employee for a general personnel in a big maintenance company has been faced through simple control-related modeling tools. The deployed model is fed by past data and does not need any critical prior knowledge or assumption on the current year. Experimental results have shown the potential of such an approach with respect to more traditional solutions.

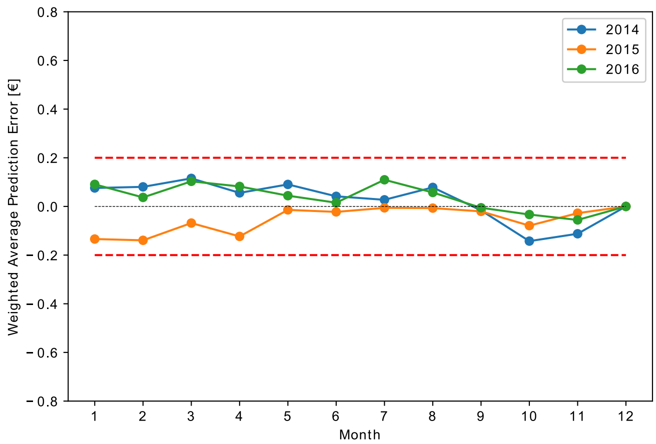

Fig. 2. Weighted Average Prediction Error; Monthly Trend per year

Future research will be devoted to the analysis of the company HR-related performance when the model is actually used to make data-driven decisions.

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