Measuring and verification of energy savings by statistical learning in manufacturing environments

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November 2015

Abstract

Industry 4.0 methodological advancements based on continuous analytics and on the sensorization of manufacturing lines make it possible to design and develop integrated systems for measurement and verification of the impact of implemented energy conservation measures (ECM) in industrial plants. The pilot study presented here has focused on developing a model of the energy consumption of the injection machines in the plant to be used to calculate the adjusted baseline. The energy savings are calculated by comparing the post-ECM energy consumption to the adjusted baseline. **Keywords:** measuring and verification; adjusted baseline calculation

1 Introduction

The term Measurement and Verification (M&V) refers to the measurements and calculations necessary for quantifying savings delivered by an Energy Conservation Measure (ECM). Savings are determined by comparing measured use before and after implementation of an ECM, making appropriate adjustments for changes in conditions [1]. Although consensus is widespread on the societal and industrial potential of the results of policies focusing on the implementation of ECMs, there is no established method of measuring the energy consumption of machine tools [2], nor for making the appropriate adjustments.

This paper presents a method for modelling the energy consumption of an injection machine. The method uses the baseline data for fitting the model and then uses the model with the post-ECM data to estimate the adjusted baseline against which to measure the energy savings.

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2 Baseline model

The mean active power (kW) in an interval is modelled as the regression line of the time (in hours) the injection machine spends in an active state within the interval. If the active time is denoted as X and the mean active power is denoted as Y, then the model is shown in equation 1 where ξ is the error term and α and β the parameters of the model. If more than one component of the injection machine have been sensorised, then there needs to be a linear regression model per component.

$$Y = \alpha + \beta X + \xi \tag{1}$$

The model's error is estimated through 10-fold cross-validation using the data for the baseline period. For each fold i, the mean error or residual, μ_i, and its variance, σ_i^2, are calculated. Then, the expected error of the model is the mean of the fold mean errors and the variance is the mean of the fold variances. Once the model error has been estimated, the linear regression model shown in equation 1 is fitted using all of the baseline data.

Given the mean active power (kW) in an interval, the mean energy (kWh) consumed in the interval is the product of the mean active power by the duration (in hours) of the interval. The mean energy consumed in any period of time that contains more than one data interval (e.g. an 8-hour work shift) is the sum of the energy consumed in the intervals contained in the period. If the energy consumed in the period is denoted by E_p, the interval duration by t_m (which is constant as the sensor takes measurements at regular intervals), and the number of intervals in the period by N_p, then the energy consumed in the period is given in equation 2, where the first term in the sum is the energy consumption estimate and the second is the error term.

$$E_p = t_m \sum_{\forall \text{ interval i in the period}} (\alpha + \beta X_i) + t_m \sum_{\forall \text{ interval i in the period}} \xi_i \tag{2}$$

By the Central Limit Theorem, if there is a sufficiently large number of intervals in the period of interest then the error term $\sum_{\forall \text{ interval i in the period}} \xi_i$ follows a normal distribution with expectancy $N_p\mu$ and variance $N_p\sigma^2$. 99.73% of the values of a normal distribution are within three standard deviations of the mean. Therefore, 99.73% of the values for the energy consumption in the period will be in the interval shown in equation 3. The endpoints of the interval are the 99.73% lower and upper bounds of the energy consumption, respectively.

$$E_p \in \left[t_m \sum_{\text{all intervals}} (\alpha + \beta X_i) + t_m \left(N_p\mu - 3 * \sqrt{N_p}\sigma \right), \; t_m \sum_{\text{all intervals}} (\alpha + \beta X_i) + t_m \left(N_p\mu + 3 * \sqrt{N_p}\sigma \right) \right] \tag{3}$$

3 Measurement of energy savings

The energy savings are calculated by comparing the observed energy consumption during the post-ECM period to the adjusted baseline. The adjusted baseline is the energy consumption estimated by applying the baseline model to the post-ECM active time data. Figure 1 shows the observed and estimated energy consumption for 8-hour shifts. The total post-ECM energy consumption is 5214.34 kWh and the adjusted baseline consumption is 6941.27 kWh. Therefore, the saving is 1726.93 kWh, i.e. 24.88% of the adjusted baseline consumption.

4 Conclusions

The proposed method achieves an excellent fit for the baseline data and, thus, provides the means to estimate the adjusted baseline against which the energy consumption for the post-ECM period can be compared. It is interesting to note that the baseline energy consumption can be modelled based only on the active time.

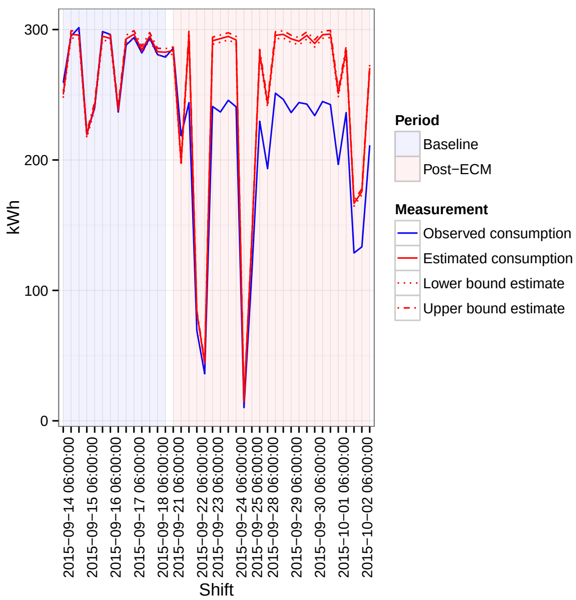

Figure 1: Estimated and observed energy consumption by 8-hour shift

References

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