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# Adaptation of fan motor and VFD efficiency correlations using Bayesian inference

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*Energy Performance Contracts (EPC) are types of agreement in which a service provider guarantees that customers' building will achieve a specified energy performance (e.i., minimum energy savings) to reduce the risk of their investment in energy efficiency improvements. EPC requires prediction of future energy consumption of the building, at the design stage, before construction or major retrofit. To this end, building energy simulations taking into account all the major energy-using components are performed. In particular, fans can contribute significantly to the total building consumption. The overall efficiency of fans is the combination of three factors: mechanical, motor and variable frequency drive (VFD). Manufacturers usually provide fan mechanical efficiency curves for a broad operating range. In contrast, motor and VFD efficiencies are generally given at rating conditions only. To represent part-load conditions, correlations are typically used to estimate motor and VFD efficiency variations, to evaluate the overall electricity consumption. The first aim of this study is to evaluate existing correlations for motor and VFD efficiency as a function of load and speed, by comparison to manufacturer data, for a vendor that has shared its detailed test data. While VFD efficiency correlations from the literature provide reasonable accuracy against real data, motor correlations under-predict actual motor efficiency at low loads. The second aim of the paper is to improve such correlations using Bayesian inference to fit the available data.*

## Introduction

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According to the International Energy Agency, the primary energy demand has doubled in the last three decades, leading to the depletion of natural resources (International Energy Agency (IEA) 2017). During the same period, $CO_2$ emissions, driven by electricity and heat generation, increased by 50%, raising serious concerns about climate change (International Energy Agency (IEA) 2017). Further, building consumption has become a prominent concern since it contributes to 40% of primary energy use in most countries (International Energy Agency (IEA) 2016). Electric motors and the systems they drive are responsible for 43%-46% of total electricity consumption, and even more in the industrial sector (64% (Waide and Brunner 2011)). In particular, fans account for around 19% of total motor electricity demand (Waide and Brunner 2011) and may account for 20% to 80% of HVAC energy consumption, especially in large commercial buildings (Krukowski and Wray 2013).

To mitigate climate change and strive for a more sustainable future, several initiatives around the world have been launched to reduce energy consumption in every sector (CERC 2017; European Union 2018). In the last two decades, Energy Performance Contracting (EPC)[2] has emerged as an effective solution to increase the energy efficiency of new and existing buildings, reducing the financial risk for customers (European Commission 2017; ICF International and National Association of Energy Service Companies 2007; Rivalin et al. 2018). To do so, the company providing the service typically needs to run energy simulations to predict energy use and cost of different designs (e.g., different types of HVAC). These detailed simulations take into account all the energy-using components in a building, at early-stage of the design. Modeling the energy consumption of building fans is a key challenge for EPC since inaccurate modeling of their efficiency can lead to substantial deviations in the estimation of the overall energy consumption (Radgen and Oberschmidt 2008).

Large fans for HVAC applications are generally driven by a motor and a variable frequency drive (VFD) to vary its output flow rate as shown in Figure 1.

2 Energy Performance Contracting is a service that provides customers with a set of energy efficiency (and sometimes renewable energy and distributed generation) measures accompanied by guarantees that the savings will be sufficient to finance the full cost of the project (ICF International and National Association of Energy Service Companies 2007).

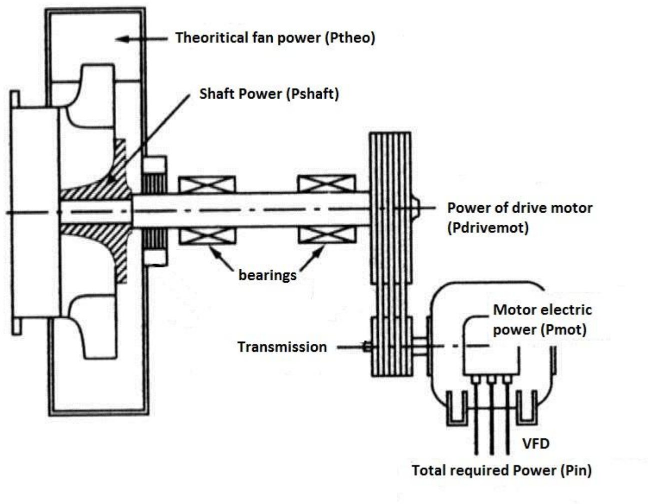



*Figure 1: Power levels of VFD-motor-fan driveline*

The required power of a VFD motor fan driveline is given by (Patel, Sheth, and kamlesh Patel 2015):

$$P_{in} = \frac{Q.H}{\eta_{VFD} \times \eta_{mot} \times \eta_{trans} \times \eta_{fan}} \tag{1}$$

Where Q is the airflow rate and H the total pressure head.

The various efficiencies refer to (Brendel 2010):

- $\eta_{fan}$ : Fan efficiency; the fan transfers only a portion of the power it receives to its shaft due to:
  - Mechanic losses dissipated in the bearings of the fan
  - Aerodynamic losses due to the passage of the discharge flange and airstream shocks at the input of the wheel, by the friction of the fluid on the wheel walls
  - Flow losses due to the clearance between the wheel and volute, creating swirls and a partial return of the fluid aspiration.
- $\eta_{trans}$ : transmission efficiency due to belt losses
- $\eta_{mot}$ : motor efficiency describing the losses inside the motor
- $\eta_{VFD}$: VFD efficiency accounting for variable frequency drive losses

Modeling a VFD-motor-fan driveline power requires knowing accurately each of the efficiencies above. Manufacturers usually provide fans or pumps mechanical efficiency curves for a broad operating range. Transmission losses are often considered negligible (Bernier and Bourret 1999), therefore $\eta_{trans} = 1$. The challenge lies in the lack of manufacturers data in most of the building projects for motor and VFD efficiencies which are usually given at rating conditions only (i.e., full load). When some manufacturer's part load efficiencies are available, fitted correlations are built from Bernier's method (Li and Wang 2017; Ma and Wang 2009; Wu et al. 2014). These correlations are built on the assumption that the efficiency of the motor can be expressed as a function of the power and the efficiency of the VFDs as a function of the speed ratio (Patel et al. 2015; Sfeir and Bernier 2005). However, in the most common case, when no data but the rated efficiency are available, correlations are generally used with this single value to evaluate fan or pump motor and variable frequency drive (VFD) efficiencies (Caillet, Rivière, and Adnot 2010; Michopoulos et al. 2015; Simpson and Marchi 2013; Vilanova and Balestieri 2015). Bernier, in his 1999 and 2005 studies, gives examples of coefficients to be used in this case, for pumping systems. Moreover, the simulation tool EnergyPlus[3] (EnergyPlus 2011) offers a built-in correlation where the coefficients are determined from DOE MotorMaster+ Data or manufacturer's data (U.S. Department of Energy (DOE) Industrial Technologies Program 2003).

One can wonder if the correlations and coefficients established in the past decades can still fit modern equipment. Indeed, the technology used in motors has evolved to reduce losses, including improvements on the continuously operated fixed-speed motor, optimization of stator and rotor design, electric material properties and quantity (for instance, copper is more and more used instead of aluminum for the rotors) (Dyess et al. 2007; Hiroyuki Mikami et al. 2011). In 2008, a European standard was published to harmonize existing motor efficiency classes aiming to support efforts to reduce energy consumption (Figure 2) (International Electrotechnical Commission 2015). This new standard defines new classes of efficiency and establishes a minimum motor performance starting from 2011, whereas no minimum efficiency was required before (Figure 3). Another recent report (Reine and Analyst 2015) shows that the efficiency of motors has significantly increased, for instance, from the late 1990s the majority of motors belonged to category "Eff3" and that they disappeared in 2002, replaced by more performant motors.

[3] EnergyPlus is a popular energy simulation tool used by researchers and industry and funded by the USA Department of Energy (Department of Energy 2017).

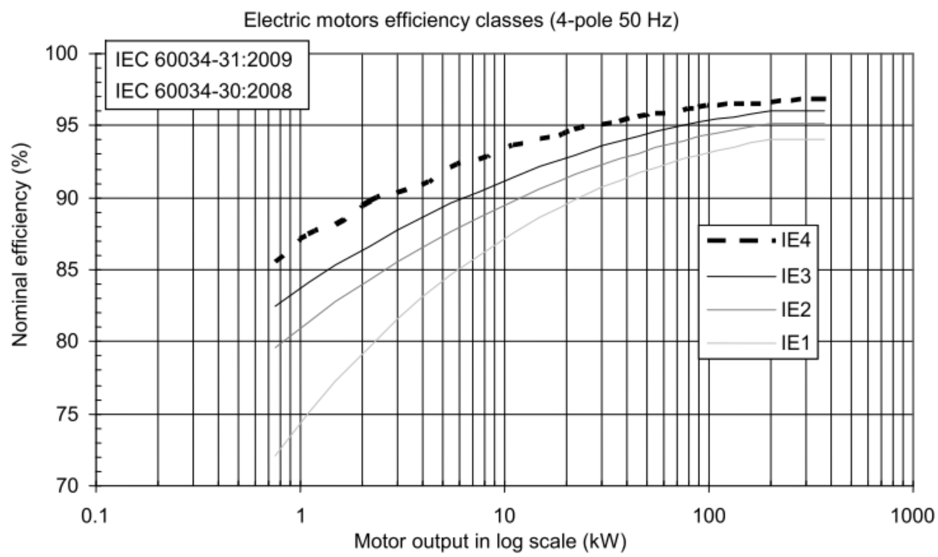



*Figure 2: Efficiency classes for four-pole motors of standard IE1, IE2, IE3 and IE4 (International Electrotechnical Commission 2015)*

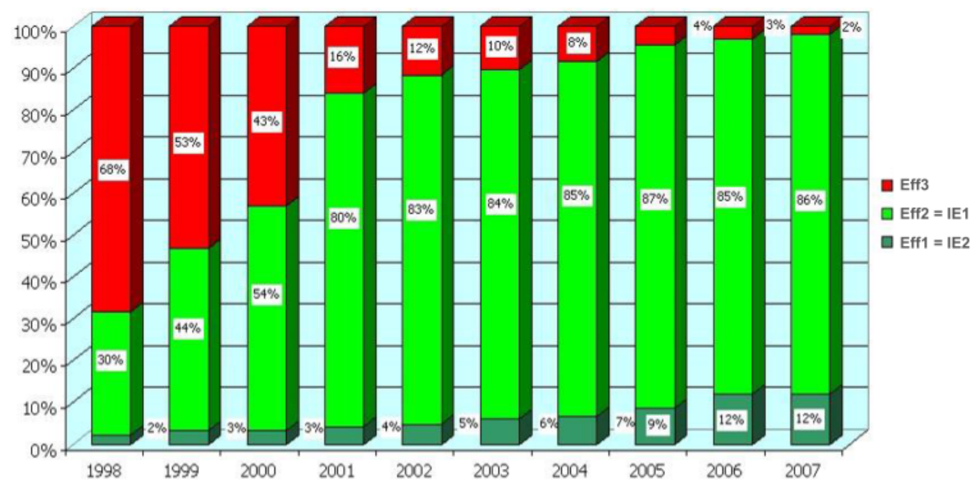



*Figure 3: European Market share for low voltage motors by efficiency class from 1998 to 2007 (Waide and Brunner 2011)*

Given the recent evolution of the market and the importance of fan efficiency in estimating energy use in buildings, this paper aims to answer two questions: 1) are Bernier's correlations for motors and VFD still working for modern products? 2) If the correlations are not adequate, how can we improve them, considering the fact that manufacturers do not provide a large amount of data?

## Background and Method

### *Existing correlations*

Bernier and Bourret (1999) and Sfeir and Bernier (2005) have modeled pump energy consumption for building applications. These methods provided VFD and motor correlations with examples of coefficients to estimate motor and VFD efficiencies as a function of, respectively, the part load and speed ratios. These correlations are used as a starting point to develop new correlations adapted to fans. Fan and pumps behave similarly because they both obey the affinity laws (Liu, Liu, and Liao 2015; Patel et al. 2015; Thambidura and Y 2013). The difference lies in the fluid they use; this allows us to use Bernier's correlation to our data.

*Bernier and Bourret Correlation (1999)*

Bernier and Bourret (1999)'s correlation which express the motor efficiency as a function of nameplate load is the following :

$$\eta_{mot} = 94.187 \times (1 - e^{-0.0904\tau}) \tag{2}$$

Where $\tau$ is the percentage of nameplate load: the ratio of shaft power supplied by the motor and power to the maximum shaft (rated kW).

The suggested correlation presents the VFD efficiency as the function of nameplate speed is the following:

$$\eta_{VSD} = 50.87 + 1.283\,\omega - 0.0142\omega^2 + 5.834 \times 10^{-5}\,\omega^3 \tag{3}$$

Where ω is the percentage of speed used as a function of the rated speed of the engine.

*Sfeir and Bernier Correlation (2005)*

Sfeir and Bernier (2005) later published an updated correlation in which motor efficiency depends on the percentage of rated load:

$$\eta_{mot} = \eta_n \times F_c \tag{4}$$

Where $\eta_n$ is the full-load efficiency of the engine for a given power rate:

$$\eta_n = 79.35 + \frac{14.3 \times P_n}{3.18 + P_n} \tag{5}$$

$P_n$ is the rated shaft power. $F_c$ is a degradation coefficient calculated as follows:

$$F_c = \frac{a \times \tau}{c + \tau} - b \times \tau \quad (6)$$

Where a, b and c are coefficients provided in a table in which the values vary according to the rated power of the engine and the motor nameplate load rate.

Bernier and Sfeir's VFD suggested correlation is:

$$\eta_{VSD} = 87.84 + 0.225 \times \omega - 0.001228 \times \omega^2 \quad (7)$$

Where $\omega$ is the percentage of the speed used in relation to the nameplate speed of the engine.

## *Manufacturer data description and method*

The first objective of the paper is to find out whether the correlations presented above are adequate to model modern motor data. To answer this question, we obtained data from a manufacturer, under the restriction of keeping its name confidential. The data represents a selection of motors and VFD used for large HVAC fans. In particular, the motor data cover 20 2014 IE3 motors characterized by four rotation speeds (1200 rpm, 1600 rpm, 2400 rpm, and 3000 rpm) and 5 powers (1 kW, 5 kW, 10 kW, 20 kW and 30 kW). Each of them is described by a table that lists for different speeds and percentage of torque, the motor losses, the VFD losses, the overall efficiency of the group (taking into account motor and VFD losses) and the maximum of combined losses (VFD and motor). Table 1 shows an example of data for a 1200 rpm speed and a rated shaft of 1 kW. The diagonals of each table (shaded cells) represent values for a constant pressure drop network.

**Table 1. Data provided by the manufacturer for a motor nameplate speed of 1200 rpm and a nameplate shaft of 1kW**

| **Motor load** | | | **Motor losses [kW] - Lmot** | | **% torque** | | | |
|---|---|---|---|---|---|---|---|---|
| Load type | fan load | | speed [rpm] | 4% | 16% | 36% | 64% | 100% |
| n min [rpm] | 1200 | | 240 | 0.05 | 0.05 | 0.06 | 0.08 | 0.14 |
| n base [rpm] | 1200 | | 480 | 0.06 | 0.06 | 0.07 | 0.1 | 0.15 |
| n max [rpm] | 1200 | | 720 | 0.07 | 0.08 | 0.08 | 0.11 | 0.16 |
| Pbase [kW] | 1 | | 960 | 0.09 | 0.09 | 0.1 | 0.13 | 0.18 |
| Tbase [Nm] | 7.96 | | 1200 | 0.11 | 0.11 | 0.12 | 0.15 | 0.21 |
| Drive load | | | Drive losses [kW] $L_{VFD}$ | | | | | |
| Icont [A] | 2.85 | | speed [rpm] | 4% | 16% | 36% | 64% | 100% |
| Imax [A] | 2.85 | | 240 | 0.03 | 0.03 | 0.03 | 0.03 | 0.04 |
| | | | 480 | 0.03 | 0.03 | 0.03 | 0.03 | 0.04 |

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | | | 720 | 0.03 | 0.03 | 0.03 | 0.03 | 0.04 |
| | | | 960 | 0.03 | 0.03 | 0.03 | 0.04 | 0.04 |
| | | | 1200 | 0.03 | 0.03 | 0.03 | 0.04 | 0.05 |
| Combined Drive & Motor(s) | | | Efficiency % | | | | | |
| | | | speed [rpm] | 4% | 16% | 36% | 64% | 100% |
| | | | 240 | 9.6 | 29.1 | 45 | 52.2 | 53.3 |
| | | | 480 | 15.5 | 41.8 | 59 | 66.5 | 67.9 |
| | | | 720 | 19.4 | 48.2 | 65.5 | 72.7 | 74.3 |
| | | | 960 | 21.6 | 51.8 | 68.7 | 76 | 77.8 |
| | | | 1200 | 22.9 | 53.7 | 70.5 | 77.7 | 79.9 |
| Worst case losses including full positive tolerance [kW] | | | | | | | | |
| | | | speed [rpm] | 4% | 16% | 36% | 64% | 100% |
| | | | 240 | 0.087 | 0.091 | 0.103 | 0.137 | 0.206 |
| | | | 480 | 0.102 | 0.104 | 0.117 | 0.152 | 0.223 |
| | | | 720 | 0.117 | 0.121 | 0.134 | 0.169 | 0.244 |
| | | | 960 | 0.136 | 0.14 | 0.154 | 0.191 | 0.27 |
| | | | 1200 | 0.159 | 0.163 | 0.178 | 0.217 | 0.3 |

VFD efficiencies are typically normalized dividing by the maximum efficiency to help compare them. The VFD efficiency and percentage of nameplate speed are calculated for each manufacturer product as:

$$\eta_{VFD} = \frac{P_{shaft} + L_{mot}}{P_{shaft} + L_{mot} + L_{VFD}} \tag{8}$$

Where $L_{mot}$ and $L_{VFD}$ are the motor and VFD losses. The shaft power can be expressed as:

$$P_{shaft} = T_{base} \times \%Torque \times speed \times \frac{2\pi}{60} \tag{9}$$

Where $T_{base}$ the base Torque [Nm], %Torque is the percentage of Tbase and $speed$ the rotation speed of the fan in revolutions per minute [rpm].

To compare the adequacy of 1999 and 2005's correlation, the maximum and minimum relative errors are computed as follows:

$$\varepsilon = \frac{\eta_{VFD}^{man} - \eta_{VFD}^{ASHRAE}}{\eta_{VFD}^{man}} \tag{10}$$

Where $\eta_{VFD}^{man}$ is the VFD efficiency given by the manufacturer and $\eta_{VFD}^{ASHRAE}$ the theoretical VFD efficiency given by 1999 or 2005 curves.

Likewise, the motor efficiency can be computed as follows:

$$\eta_{mot} = \frac{P_{shaft}}{P_{shaft} + L_{mot}} \tag{11}$$

The relative error between data and correlation is calculated similarly :

$$\varepsilon = \frac{\eta_{mot}^{man} - \eta_{mot}^{ASHRAE}}{\eta_{mot}^{man}} \tag{12}$$

As no standard or guideline defining the acceptable threshold of error for motor and VFD efficiencies estimation, we followed industry expertise which uses a threshold of 20% error between the estimated, and the actual efficiency is arbitrarily adopted as the success criterion (Rivalin, Cogné, and Caciolo 2013). Above 20% error, it is considered that the estimation could lead to a non-compliance of the energy performance contracting.

## *Bayesian inference*

Literature has shown that researchers have a good understanding of the general relationships governing fan efficiency (section “Existing correlations”), but they lack measured manufacturer data (section “Manufacturer data description and method”). If our test (sections “Testing VFD efficiency correlations” and “Testing motor efficiency correlations”) proves these correlations to be outdated, Bayesian statistics will be an effective technique to develop new ones.

Bayesian inference is a method to update a knowledge-based model with experimental observations (Gregory 2005). The Bayesian probability is seen as a “degree of belief” of the phenomena (O’Hagan 2004) which is revised if new information (observation) is provided. Thus, “uncertainty” in the Bayesian paradigm can describe both the lack of knowledge of a parameter and its variability. In practice, to set a Bayesian calibration, a model linking data to parameters is build. Then, a formulation of uncertainty knowledge about the parameters is provided “a priori”. The model is combined with experimental values through the Bayes formula to obtain the “a posteriori” distribution (Parent and Bernier 2007). Bayesian inference can be seen as an inversion problem as it permits to understand the causes through the effects given by the observation (Christian P. Robert 2007).

The Bayesian paradigm can also be seen as a mathematical formalization of the usual scientific process: first, an assumption is made, then it is compared to observations to validate or update the assumption. The particularity of this method lies in associating a confidence level with the starting hypothesis (the "a priori"). That allows, on the one hand, to nuance expert information with data or, on the other hand, to ponderate a small dataset with strong expertise. Therefore, this method is suitable for our case, where we have a strong knowledge (Bernier's correlations) that suited data for the past decades and a few new data from a more recent technology.

Let D be the data and θ the model parameter. The “a priori” distribution P(θ), provided by an expert, describes the belief (or uncertainty) given to the value of θ. As it is impossible to know the “true” distribution of parameter θ, we consider the observation data of a given statistical realization P(D|θ). Bayes’ theorem aims to combine those distributions to obtain the “a posteriori” distribution knowing the data: P(θ|D) and so, update the “a priori” distribution (Kuss et al. 2005) (Figure 4).

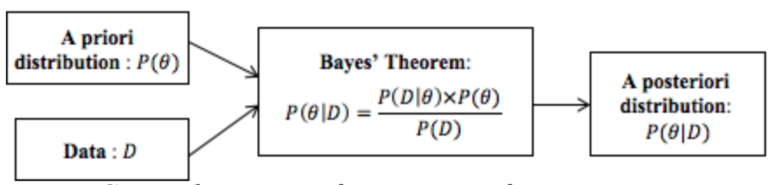



*Figure 4: General process of Bayesian Inference*

Bayesian inference has received increasing attention as an inverse method to calibrate unknown parameters in building energy models by taking into account prior information on the uncertain inputs while using a small amount of evaluations from a time-consuming building model (Heine, Choudhary, and Petersen 2017)(Tian et al. 2018)(Yuan, Nian, and Su 2017) or a small amount of observed values (Lim and Zhai 2018)(Sokol, Cerezo Davila, and Reinhart 2017)(Chong and Menberg 2018)(Kristensen, Choudhary, and Petersen 2017).

Our paper aims to calibrate a sub-system of a whole building energy model, for which a few data are available, and we want to include the expertise that has been formulated and used in the industry for decades. Moreover, the result may be used in further sensitivity and uncertainty analysis un larger building energy models to generate energy performance contracting. In this context, the Bayesian framework is a perfect candidate as it not only results in a deterministic value but outputs probabilistic densities modeling uncertainty around the parameter, given the prior and the possible measurement or modeling errors.

## Results

### *Testing VFD efficiency correlations*

Figure 5 shows normalized efficiency for each product provided by the manufacturer, based on equation (8), in comparison to 1999 (dashes) and 2005 (dots) correlations. Note that for each VFD, we do not have any efficiency data under 20% of speed rotation.

The normalization method is the following :

$$\eta_{VFD}^{normalised}(\%speed) = \frac{\eta_{VFD}(\%speed)}{\eta_{VFD}(100\%\,speed)} \tag{13}$$

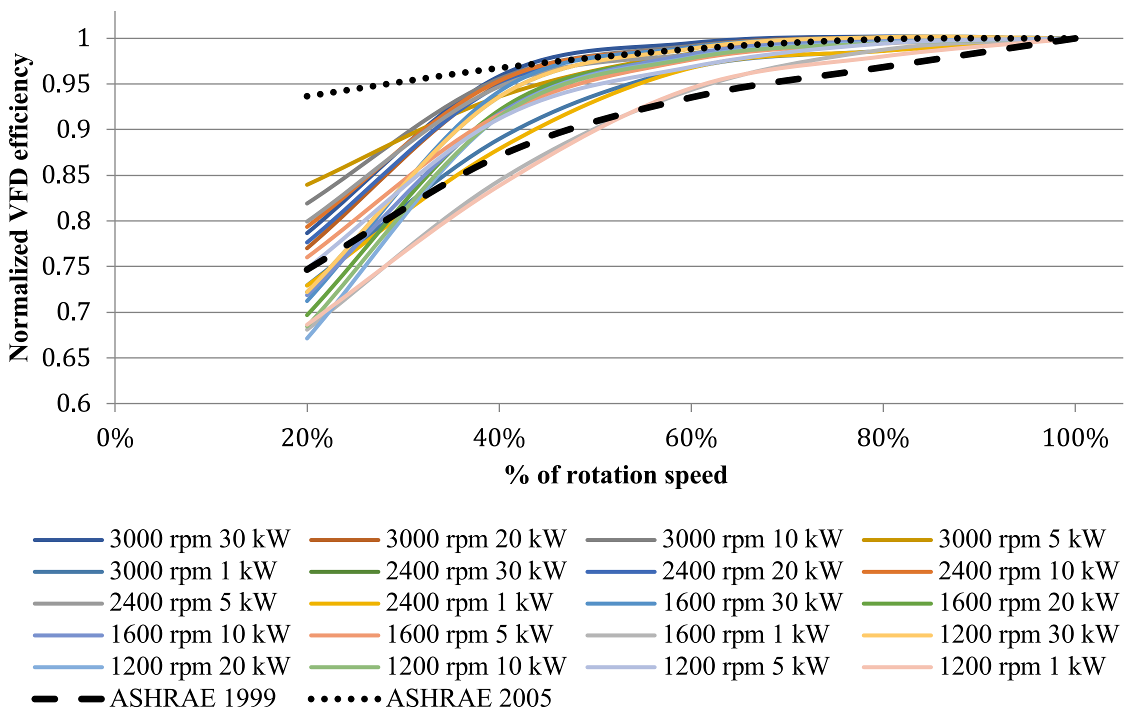



*Figure 5: Normalized VFD manufacturer 1999 and 2005 efficiencies*

We compute the error ε using equation (10). Positive and negative values of ε represent respectively relative errors for curve lying above and below the reference curve. Figure 6 shows that 1999 correlation never exceeds 12% of relative error for low nameplate speed rate. The maximum and minimum relative errors are relatively symmetric showing this correlation represents our data adequately. Instead, the 2005 correlation shows results exceeding 35% of relative error for low loads, which is above our 20% error criteria. Also, the results are predominantly negative, indicating that the correlation tends to overestimate the manufacturer efficiency curves. The 1999 correlation is more adapted to model VFD efficiency based on the percentage of nameplate speed. 1999 ASHRAE correlation provides an error less than 12%, below our 20% error criteria; thus the VFD correlation will not be modified.

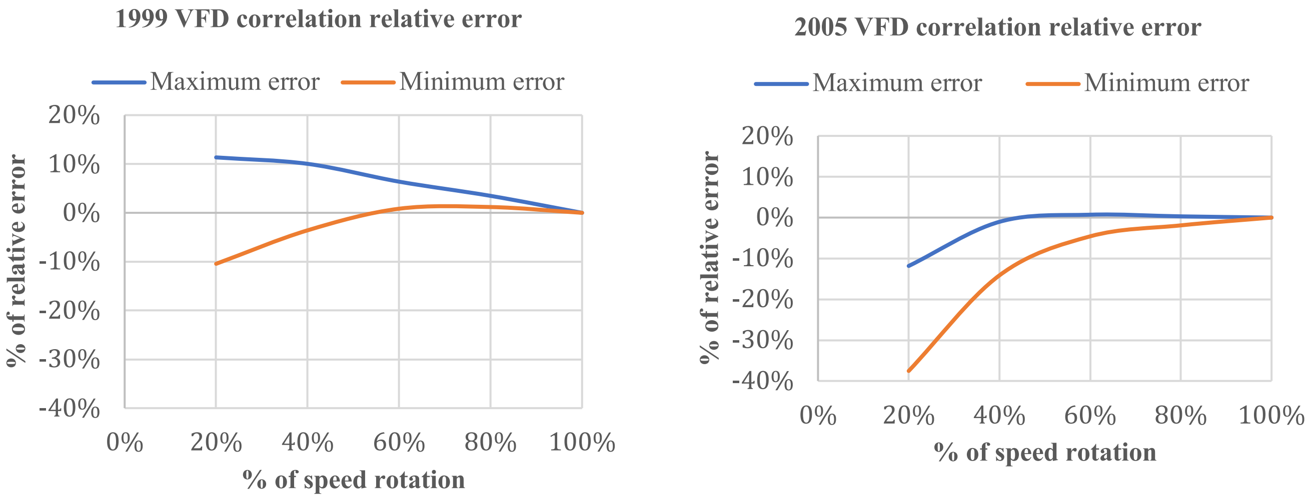



*Figure 6: Percent relative errors of VFD efficiencies for 1999 and 2005 correlations*

## ***Testing motor efficiency correlations***

Figure 7 shows every normalized motor efficiency and 1999 (dashes) and 2005 (dots) correlations. Note that for each motors, the efficiency data starts at 0.8% of full load.

As previously, we normalize the efficiencies so that all curves can have a 100% asymptote.

The normalization method is the following :

$$\eta_{mot}^{normalised}(\%speed) = \frac{\eta_{mot}(\%speed)}{\eta_{mot}(100\%\ speed)} \tag{14}$$

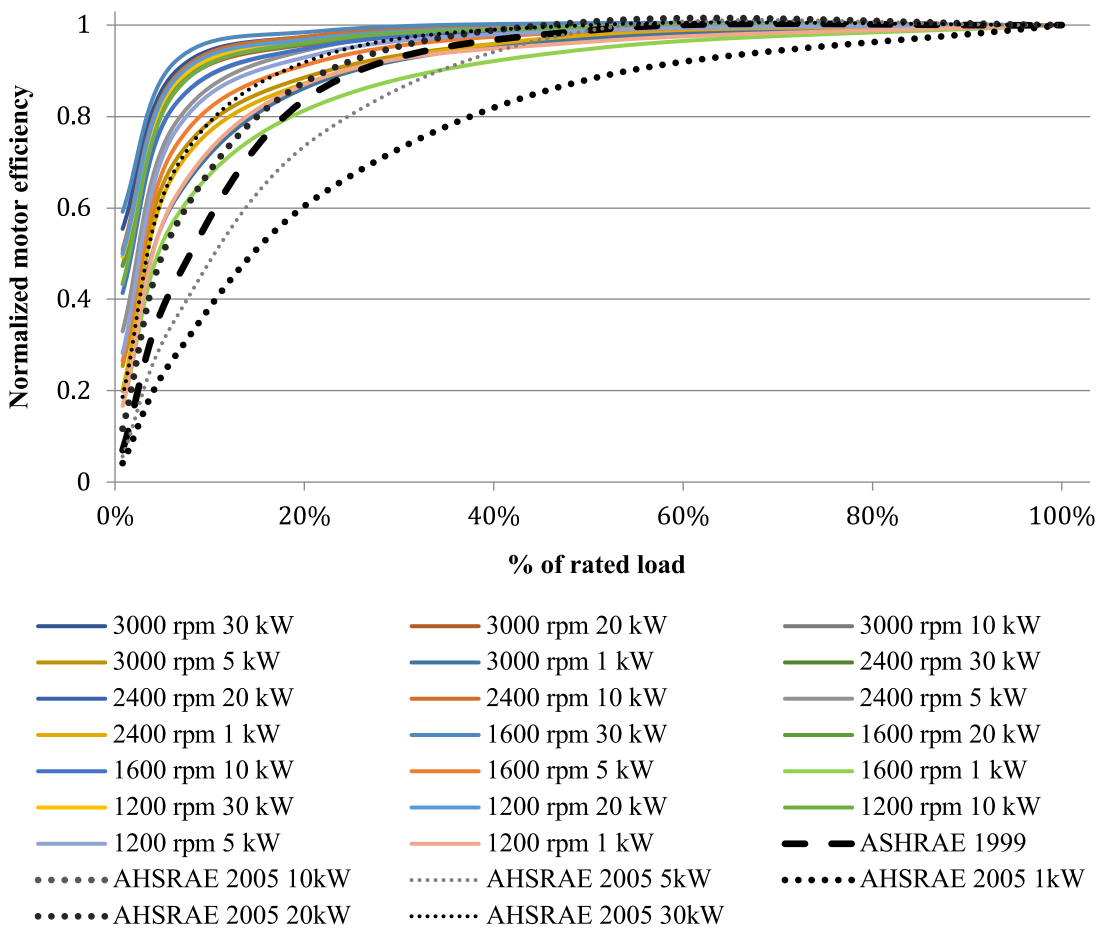



*Figure 7: Normalized motor manufacturer 1999 and 2005 efficiencies*

The 2005 correlation seems to underestimate the efficiency. As previously, we calculated relative errors to determine the validity of the correlations for our data (Figure 8).

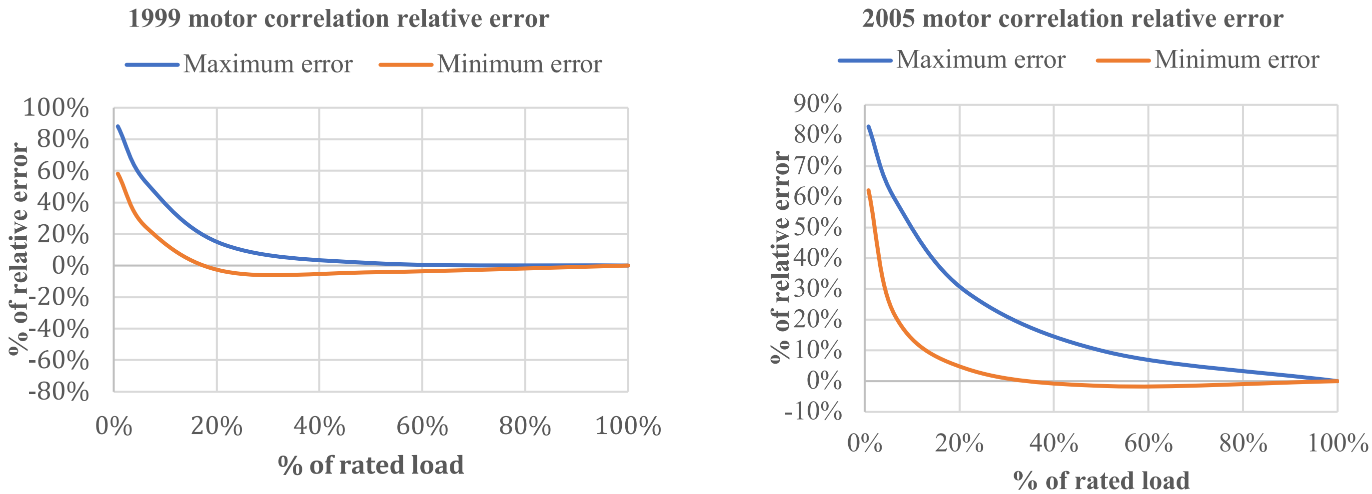



*Figure 8: Percent relative error of motor efficiencies for 1999 and 2005 correlations*

The correlations show a percent relative error up to 80%, far from our 20% error threshold. Thus, none of the correlations is acceptable for our fan motor data. As figures 6 and 8 show, all the correlations tested are accurate (under our 20% error criteria) for rated loads higher than 40%. As expected, the correlations' accuracy decreases dramatically under 40% of the rated load. Then, to characterize if a correlation is suitable or not; we'll focus on the maximum and average error on efficiencies for low rated loads (i. e under 40% of rated load). Table 2 summarizes the results of the evaluation of existing correlations using manufacturer data for modern motors. For VFD, the 1999 correlation is adopted, because the maximum error under 40% of the rated load is 11%. However, none of the correlations are acceptable for the motors, as the max and average errors for low loads are above 40% of error. As both errors for 1999 and 2005 motor correlations are large (Table 2), we will adapt both of them with Bayesian inference to select the best one. We will start adjusting the 1999 motor correlation as the corresponding VFD correlation fits the data better.

**Table 2. Summary table of maximum errors in absolute values for correlations from the literature applied to the new dataset**

| | 1999 correlation | | 2005 correlation | |
|---|---|---|---|---|
| | Max error for loads below 40% of rated load | Average error for loads below 40% of rated load | Max error for loads below 40% of rated load | Average error for loads below 40% of rated load |
| Motor | 88% | 44% | 83% | 43% |

| | | | | |
|---|---|---|---|---|
| VFD | 11% | 6% | 38% | 16% |

## *Use of Bayesian inference to improve correlations*

*Bayesian inference use in 1999 motor efficiency correlation*

In the previous section, we compared 2005 and 1999 motor correlations with fan manufacturer's data, finding relative errors that exceeded 40% (Table 2), for low loads. As we do not have many data points, but both correlation shapes seem to track the data, we will use the same mathematical expression for the 1999 correlation and apply Bayesian statistics to correct the coefficients and to fit the data (see section "*Bayesian inference*"):

$$\eta_{mot} = a \times (1 - e^{-b \times \tau}) \tag{15}$$

The coefficient b corresponds to the growth rate of the curve. WinBUGS software (Lunn, D.J., Thomas, A., Best, N. y Spiegelhalter 2000) is used to carry out the Bayesian regression by means of Markov Chain Monte Carlo (MCMC) (Gilks, Richardson, and Spiegelhalter 1996) to new "a" and "b" coefficients of the "a posteriori" distributions.

To create the "a priori" distribution, we define Gaussian with a mean (expertise) and a standard deviation (confidence). The means of the a priori distributions are the value Bernier gave to the coefficients; we consider this is our "expertise" (Bernier and Bourret 1999). The confidence of the b coefficient is weak because it does not fit the manufacturer data (Figure 7). To the contrary, we give strong confidence to the "a" coefficient as it relates to the full load of the motor.

The Bayesian model (likelihood) is formulated as :

$$Y_i \sim \mathcal{N}(\eta_{mot}, \sigma^2)$$

A Normal distribution is chosen to express the prior information for a and b and a Gamma distribution for the precision $\tau = \sigma^{-2}$. Hence,

$$a \sim \mathcal{N}(94.187{,}5)$$

$$b \sim \mathcal{N}(0.0904, 400)$$

$$\tau \sim \Gamma(0.01{,}0.01)$$

Figure 9 and 10 show the “a priori” and “a posteriori” distribution WinBUGs obtain for both coefficients.

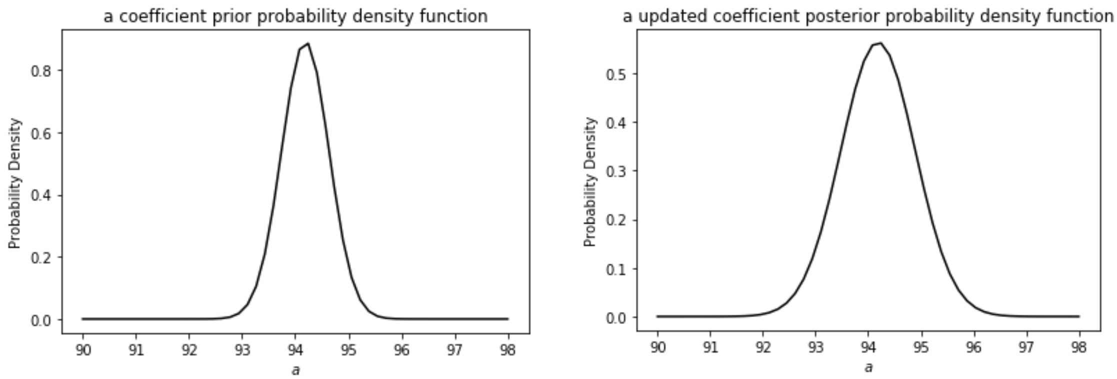



*Figure 9: Coefficient “a” a priori (left) and updated with data (right)*

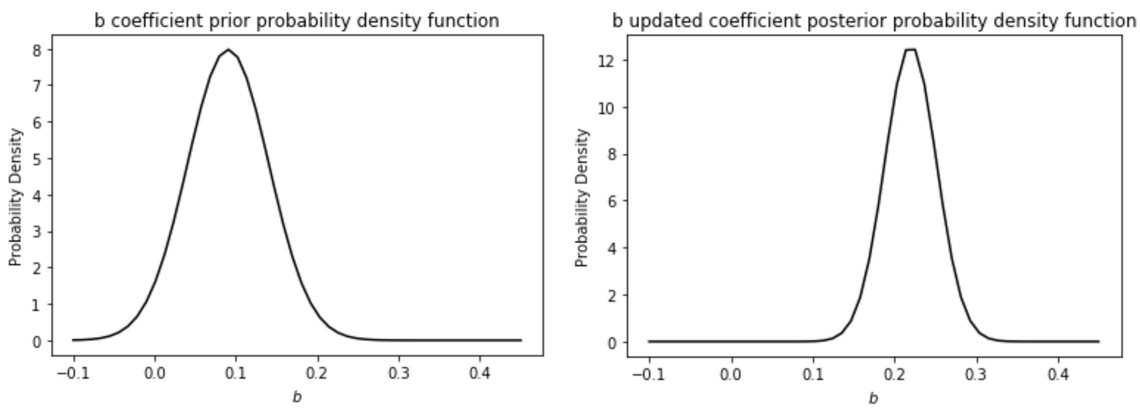



*Figure 10: Coefficient b a priori (left) and updated with data (right)*

As we associated the “a” coefficient with strong confidence (see figure 9), the posterior probability, updated with measured data has the same mean value (94.19) with a wider standard deviation induced by the observation. On the contrary, b coefficient has been adjusted: median is updated from 0.0904 to 0.22, and the standard deviation is reduced (figure 10). The Markov Chain Error (MC Error) is the error computed by different samples simulated by the Markov Chain. Table 3 shows the MC Error for coefficients a and b.

**Table 3. Summary Statistics**

| Density | | mean | std | MC Error |
|---|---|---|---|---|
| a | prior | 94.19 | 0.44 | 1E-3 |
| | posterior | 94.19 | 0.7 | 1.5E-3 |
| b | prior | 0.0904 | 0.05 | 1.2E-4 |
| | posterior | 0.22 | 0.03 | 1.15E-4 |

Then, the result of the new curve is:

$$\eta_{mot} = 94.19 \times (1 - e^{-0.22\times\tau}) \tag{16}$$

Figure 11 shows the new correlation compared to manufacturer data.

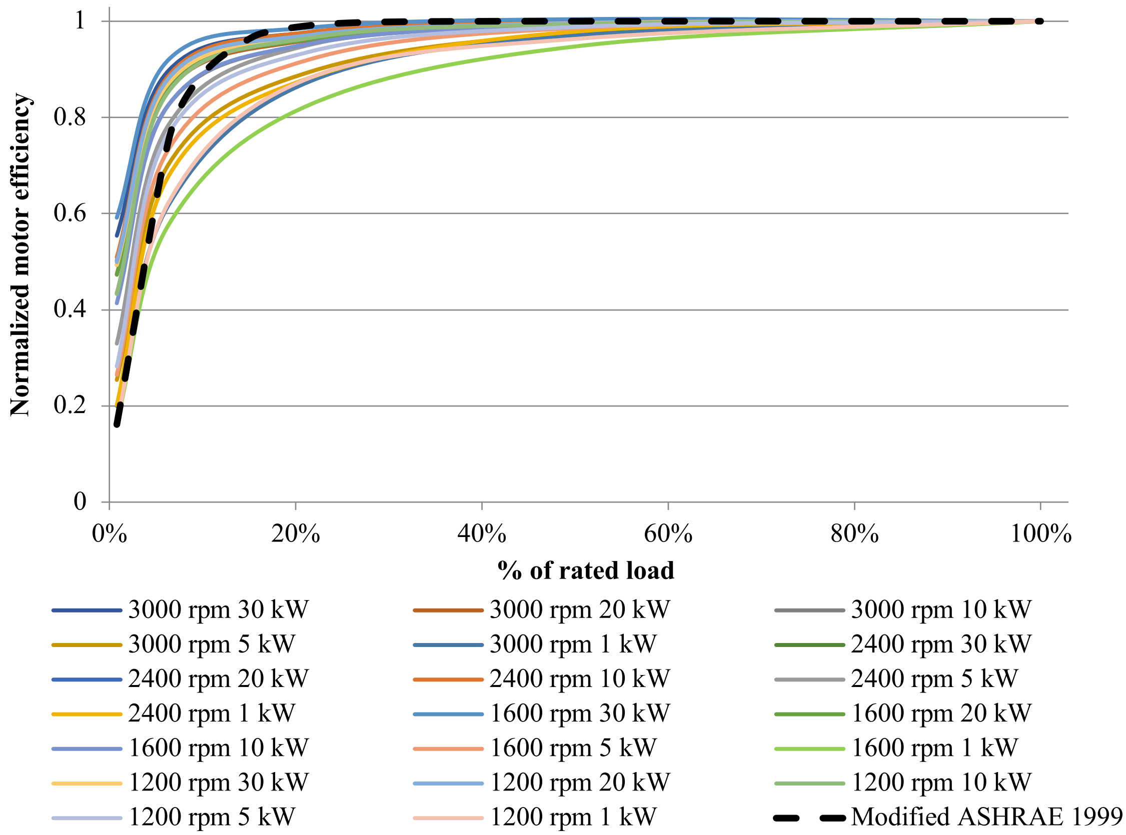



*Figure 11: Normalized motor efficiencies and new correlation*

The relative error generated by this adapted correlation is displayed in Figure 12.

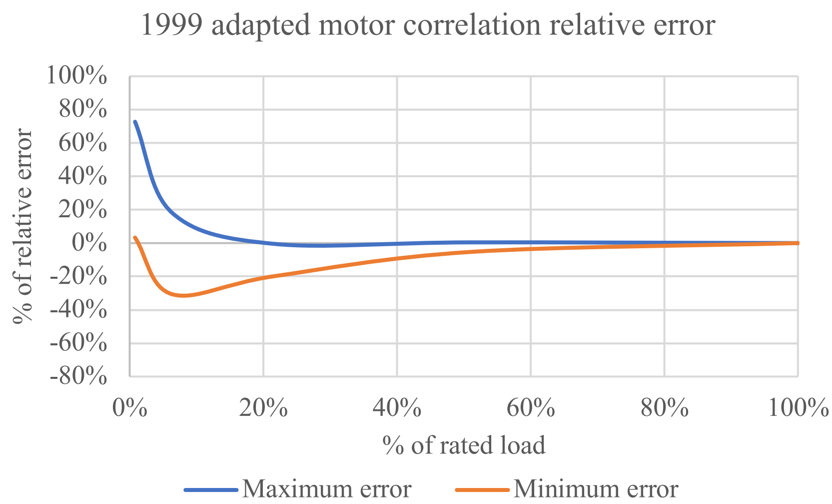



*Figure 12: Percent relative errors of motor efficiencies for 1999 modified correlation*

We can see that the coefficient adaptation gives a better accuracy under 40%, but is still above 20% of error, especially at very low loads. This is due to the fact that we try, as Bernier first did, to fit the correlation to a wide range of power shafts and rotation speeds. Thus, as the accuracy is still not satisfying, we try to adapt in the following section 2005 correlation which is more adapted to a wide range of power shafts.

*Bayesian inference use in 2005 motor efficiency correlation*

The 2005 correlation provides different sets of coefficients depending on the motor power. This correlation is a product of 2 terms: equation (5) that expresses the full-load efficiency of the engine for a given power, and (6) which is a degradation coefficient given the percentage of nameplate load.

As table 4 shows, equation (5) fits very well our data, with less than 2% of error for the efficiency at full-load as a function of the power rate.

**Table 4. Comparison of theoretical full-load efficiency with our data**

| Shaft power (kW) | Average of the full-load efficiency data | Theoretical full-load efficiency (5) | Error |
|---|---|---|---|
| 1 | 83% | 83% | 0% |
| 5 | 88% | 88% | 0% |
| 10 | 90% | 92% | 2% |
| 20 | 92% | 94% | 2% |
| 30 | 92% | 94% | 2% |

Given the errors of this correlation compared to our manufacturers' data (see section "Testing motor efficiency correlations") that are not due to (5) (see Table 4) we shall have to adapt equation (6). This equation expresses the degradation coefficient Fc, where a, b and c, in the 2005 correlation are given in a table resulting from experimental data that we will use as means to our a priori density.

Using a similar approach of section "Bayesian inference use in 1999 motor efficiency correlation", we use WinBUGS to adjust the coefficients In the 2005 correlation, coefficients are given depending on a range of motor power (see Table 5). Given the significant error of the 2005 correlation (as in Figure 9), the "a priori" distributions created for each coefficient of the table are associated with low confidence.

**Table 5. Original ("a priori") coefficients to be used in (6) of 2005 correlation (Sfeir and Bernier 2005)**

| Motor Power (HP) | a | | | b | | | c | | |
|---|---|---|---|---|---|---|---|---|---|
| | Mean | Std | Mc error | Mean | Std | Mc error | Mean | Std | Mc error |
| 1 | 144.56 | 31.62 | 0.09 | 0.16 | 0.1 | 3.13E-4 | 26.27 | 10 | 0.03 |
| 1.5-5 | 220.86 | 31.62 | 0.09 | 0.64 | 0.1 | 3.15E-4 | 35.56 | 10 | 0.03 |
| 7.5-10 | 145.02 | 31.62 | 0.09 | 0.28 | 0.1 | 3.07E-4 | 14.58 | 10 | 0.03 |
| 15-25 | 124.74 | 31.62 | 0.09 | 0.17 | 0.1 | 3.02E-4 | 7.75 | 10 | 0.03 |
| 30-60 | 111.99 | 31.62 | 0.07 | 0.0798 | 0.031 | 7.03E-5 | 4 | 10 | 0.07 |

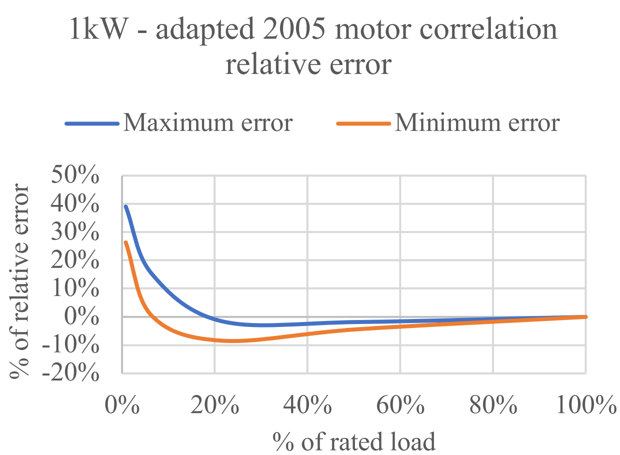
As previously, we update the "a priori" distributions with data for each the motors. The mean-value of the "a posteriori" distribution gives us new coefficients shown in table 6.

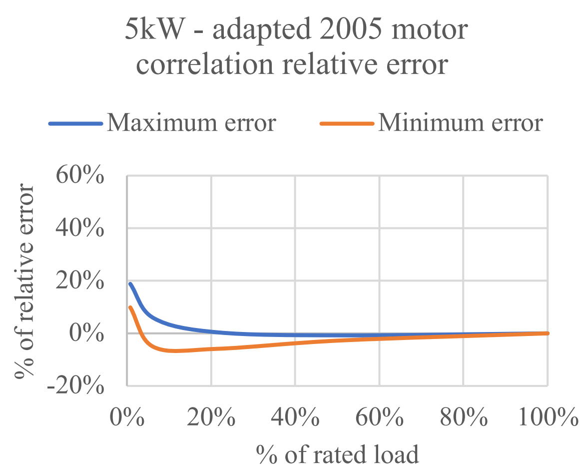
**Table 6. New ("a posteriori") coefficients to be used in (6) obtained by Bayesian inference**

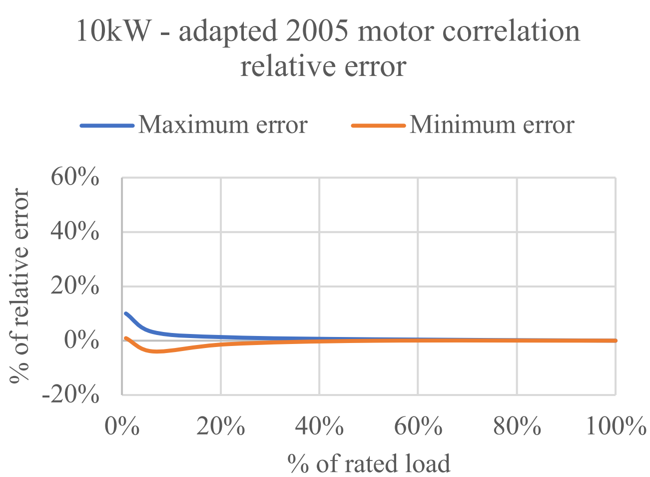
| Motor Power (HP) | a | | | b | | | c | | |
|---|---|---|---|---|---|---|---|---|---|
| | Mean | Std | Mc error | Mean | Std | Mc error | Mean | Std | Mc error |
| 1 | 1.23 | 0.82 | 0.015 | 0.00154 | 0.0029 | 1.22E-4 | 7.126 | 2 | 0.018 |
| 5 | 1.089 | 1 | 0.013 | 6.35E-04 | 0.0035 | 1.05E-4 | 3.021 | 1.44 | 0.07 |

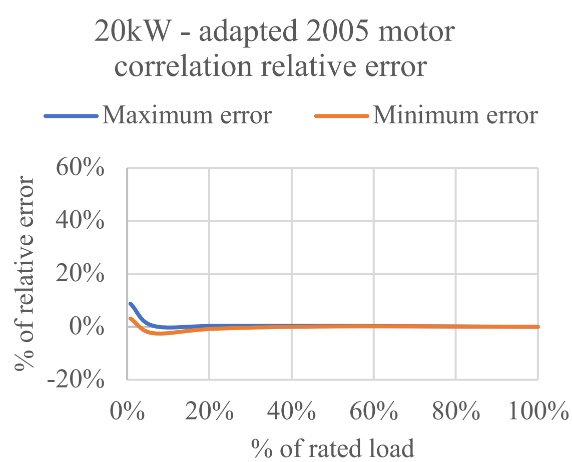
| | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| 10 | 1.02 | 0.8 | 0.007 | 8.95E-05 | 0.0022 | 4.64E-5 | 1.192 | 0.45 | 0.02 |
| 20 | 1.012 | 0.6 | 0.006 | 2.47E-05 | 0.0015 | 4.32E-5 | 0.9681 | 0.4 | 0.013 |
| 30 | 1.018 | 0.4 | 0.006 | 1.17E-04 | 0.0018 | 5.94E-5 | 0.8138 | 0.32 | 0.07 |

Figure 13 shows a clear reduction of the error over the previous coefficients for each motor power. With the exception of 1kW Motor power, that peaks at 40% error, for all the other motors the error is below 20% (e.g., 14% for 30 kW Motor). The larger the motor, the smaller the error is.



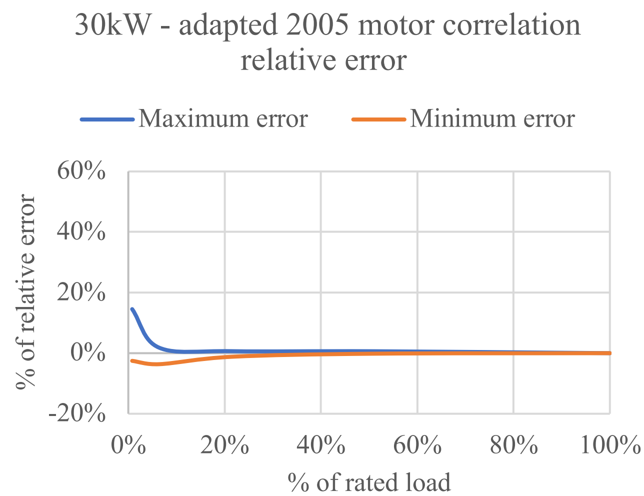



*Figure 13: Percent relative errors of motor efficiencies for 2005 modified correlation*

With the dataset provided by the manufacturer, we do not have enough data to create a correlation for power ranges similar to what is provided by the literature (e.g., 2005 correlation, Figure 7). Therefore we propose a new correlation to generalize these findings to cases when motor power is unknown or not equal to one of our measured values.

To estimate new correlation coefficients, we calculated the mean of the ASHRAE coefficients, and then applied Bayesian inference considering all the data. The result is a general degradation correlation usable for all motor powers that can be used as in equation (4) in cases when the motor power is unknown, but the full-load efficiency is given:

$$F_c = \frac{0.982 \times \tau}{1.309 + \tau} + 3.59 \, . \, 10^{-4} \times \tau \quad (17)$$

The error of this generalized equation is shown in Figure 14. The generalized 2005 correlation shows less than 20% of error for all the motors from 40% of rated load, and seems to be well balanced: real data are both above or below the estimation, which avoids continuous over or under-estimations. Moreover, the average error below 40% of the rated load is better with this approach than using the modified 1999 ASHRAE correlation (see table 6).

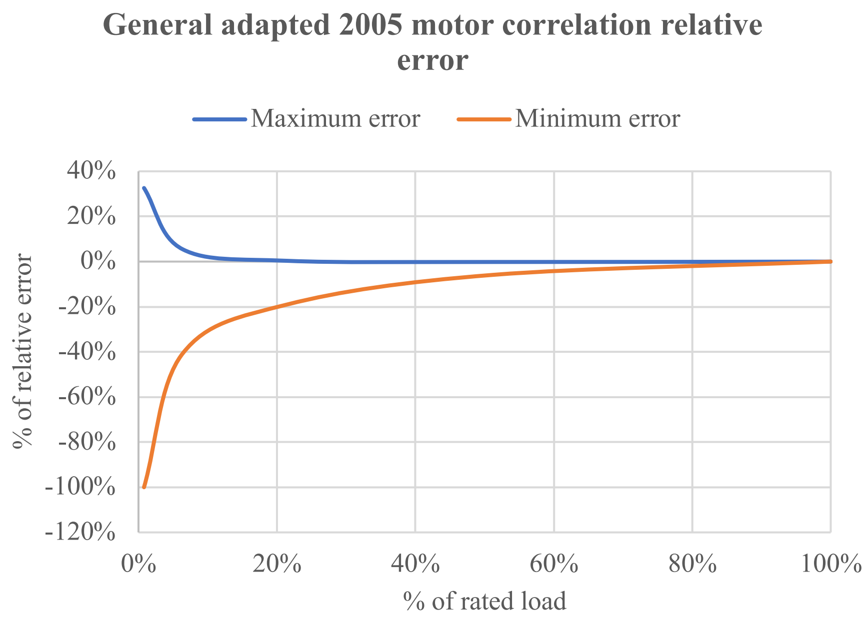



*Figure 14: Error of the general degradation correlation when used with known data*

Table 6 summarizes the results obtained using Bayesian statistics to adapt the correlation equations.

| Table 6. Summary of the improvement of new correlations testes on modern motor data | | | |
|---|---|---|---|
| **Adapted motor efficiency correlation** | **1999** | **2005 (using available motor sizes)** | **2005 (generalized)** |
| **Figure** | Figure 12 | Figure 13 | Figure 14 |
| **Max error for load below 40% of rated load** | 71% | 1 kW: 39%<br>5 kW: 19%<br>10 kW: 10%<br>20 kW: 8%<br>30 kW: 14% | 100% |
| **Average error for load below 40% of rated load** | 24% | 1 kW: 14%<br>5 kW: 6%<br>10 kW: 3%<br>20 kW: 2%<br>30 kW: 3% | 18% |

## Discussion and Conclusion

The first goal of this study was to evaluate pump correlations for motors and VFD established in 1999 and 2005 to estimate the performance of modern (2014) motors. 1999 VFD correlation fit our data with less than 15% error without any modification and thus can be used for modern products. However, 1999 and 2005 correlations for motor efficiency generate large errors, when applied to new motors. This was expected as motor technologies, and new standards have led to significant improvements in performance.

To reduce the error, we proposed an approach to correct the existing equations (second goal). Since we had a small dataset but strong "expertise" provided by correlation being used for several years, we applied Bayesian statistics to update both correlations and identify new coefficients. The Bayesian paradigm is widely used in domains where uncertainty is high but physical modeling (using equations) is rarely possible, like in medicine or finance. However, we suggest its use in domains where physical modelization is possible, but technology is constantly evolving. In this case, a law's coefficients or parameters can be updated to a few real-world data. The strength of Bayesian statistics lies in the fact that we can implicitly reuse previous studies by giving confidence to the coefficients of the laws and update them with the current data. The more general we want the correlation to be, the more data we would need.

Realizing that Bernier's equation errors were particularly large at low loads we used Bayesian statistics to update the 2005 degradation factor Fc. When the power motor was known and between 1kW and 30kW, we created new correlations to calculate the degradation factor (see table 5), leading to less than 20% of average error for low load. To provide reliable values when motor power is unknown or out of these ranges, we suggested using our adaptation of 2005 correlation with generalized coefficients, that leads to an average error of 25% for low load, but it is more widely applicable.

The new correlations can be used in a building model to predict energy consumption: if the shaft power is known, the modeler can use equation (4) with the new coefficients provided in Table 5. If even the shaft power is not known (early design process), we suggest using the generalized 2005 correlation with the new degradation coefficient (16) in (4). Using these correlations prevents overestimations of the fan energy consumption and improves overall energy prediction accuracy. An accurate prediction of fan efficiency and fan power is critical in EPC since fans contribute significantly to the total energy use of a building and a company's profit can be negatively impacted by inaccurate predictions.

Bayesian methods has been used to calibrate building energy models in the literature, but we haven't met this method applied to subsystems. More broadly this technique can be used by researchers or engineers to update model coefficients using new data from manufacturers and taking advantage of the existing "expertise" provided by previous engineering and statistical models.

Future work should test these new correlations with a broader manufacturer dataset to validate the new 2005 correlations obtained here. In addition, we would like to explore the use of this approach with other systems, like heat pumps (COP curves) and chilled beams (induction ratios).

## References


Bernier, Michel A. and Bernard Bourret. 1999. “Pumping Energy and Variable Frequency Drives.” *ASHRAE Journal* (December):1–4.

Brendel, Michael. 2010. “The Role of Fan Efficiency in Reducing HVAC Energy Consumption.” *AMCA Internation*.

Caillet, J., P. Rivière, and J. Adnot. 2010. “Procedures to Identify Energy Conservation Opportunities Applied to HVAC System: Example of VSD of Chilled Water Pumps.” *Clima 2010, 10th REHVA World Congress*.

CERC. 2017. “U.S.–China Clean Energy Research Center.” Retrieved (http://www.us-china-cerc.org/).

Chong, Adrian and Kathrin Menberg. 2018. “Guidelines for the Bayesian Calibration of Building Energy Models.” *Energy and Buildings* 174:527–47. Retrieved (https://doi.org/10.1016/j.enbuild.2018.06.028).

Christian P. Robert. 2007. *The Bayesian Choice: From Decision-Theoretic Foundations to Computational Implementation*.

Department of Energy. 2017. “EnergyPlus Project Webpage.” https://www.energy.gov/eere/buildings/downloads/en.

Dyess, Nicole Kaufman, Emmanuel Agamloh, D. Ph, and Advanced Energy. 2007. “Copper Rotor Motors: A Step toward Economical Super-Premium Efficiency Motors?” *ACEEE Summer Study on Energy Efficiency in Industry* 2:65–74.

EnergyPlus. 2011. *EnergyPlus Engineering Reference - The Reference to EnergyPlus Calculations*.

European Commission. 2017. “Eurocontract - European Platform for the Promotion of Energy Performance Contracting (EUROCONTRACT).” Retrieved (https://ec.europa.eu/energy/intelligent/projects/en/projects/eurocontract).

European Union. 2018. “Intelligent Energy Europe.” Retrieved (https://ec.europa.eu/energy/intelligent/about/concerted-actions/).

Gilks, W., S. Richardson, and D. Spiegelhalter. 1996. *Markov Chain Monte Carlo in Practice*. Chapman and Hall/CRC. Retrieved (978-0412055515).

Gregory, Phil. 2005. *Bayesian Logical Data Analysis for the Physical Sciences*. edited by Cambridge University Press. Cambridge.

Heine, Martin, Ruchi Choudhary, and Steffen Petersen. 2017. “Bayesian Calibration of Building Energy Models : Comparison of Predictive Accuracy Using Metered Utility Data of Different Temporal Resolution.” *Energy Procedia* 122(September):277–82. Retrieved (http://dx.doi.org/10.1016/j.egypro.2017.07.322).

Hiroyuki Mikami, Kazumasa Ide, Yukiaki Shimizu, Masaharu Senoo, and Hideaki Seki. 2011. “Historical Evolution of Motor Technology.” *Hitachi Review* 60(1).

ICF International and National Association of Energy Service Companies. 2007. “Introduction to Energy Performance Contracting.” (October). Retrieved (http://www.energystar.gov/ia/partners/spp_res/Introduction_to_Performance_Contracting.pdf).

International Electrotechnical Commission. 2015. *IEC 60034-30-1 Ed. 2 : Rotating Electrical Machines - Part 30-1: Efficiency Classes Of Line Operated Ac Motors (IE Code)*.

International Energy Agency (IEA). 2016. “Building Energy Performance.” *International Energy Agency*. Retrieved (http://www.iea.org/etp/buildings/).

International Energy Agency (IEA). 2017. “Key World Energy Statistics.” *International Energy Agency*.

Kristensen, Martin Heine, Ruchi Choudhary, and Steffen Petersen. 2017. “Bayesian Calibration of Building Energy Models: Comparison of Predictive Accuracy Using Metered Utility Data of Different Temporal Resolution.” *Energy Procedia* 122:277–82. Retrieved (https://doi.org/10.1016/j.egypro.2017.07.322).

Krukowski, Andrea and Craig P. Wray. 2013. “Standardizing Data for VFD Efficiency.” *ASHRAE Journal* 55(6):16:26.

Kuss, Malte, Max Planck, Biological Cybernetics, Frank Jäkel, and Felix A. Wichmann. 2005. “Bayesian Inference for Psychometric Functions Bayesian Inference For.” *Journal of Vision* 5(5):478–92. Retrieved (http://www.journalofvision.org/content/5/5/8.short).

Li, Hangxin and Shengwei Wang. 2017. "Probabilistic Optimal Design Concerning Uncertainties and On-Site Adaptive Commissioning of Air-Conditioning Water Pump Systems in Buildings." *Applied Energy* 202:53–65.

Lim, Hyunwoo and Zhiqiang (John) Zhai. 2018. "Influences of Energy Data on Bayesian Calibration of Building Energy Model." *Applied Energy* 231(September):686–98. Retrieved (https://www.sciencedirect.com/science/article/pii/S0306261918314673).

Liu, Lanbin, Yameng Liu, and Jiajun Liao. 2015. "Issues of Pumps and Fans in HVAC Systems - Part 2." *World Pumps* 2015(3):38–41.

Lunn, D.J., Thomas, A., Best, N. y Spiegelhalter, D. 2000. "WinBUGS- A Bayesian Modelling Framework: Concepts, Struture, and Extensibility." *Statistics and Computing* 10:325–37.

Ma, Zhenjun and Shengwei Wang. 2009. "Energy Efficient Control of Variable Speed Pumps in Complex Building Central Air-Conditioning Systems." *Energy and Buildings* 41(2):197–205.

Michopoulos, Apostolos, Aikaterini Tsikaloudaki, Vasiliki Voulgari, and Theodoros Zachariadis. 2015. "Analysis of Ground Source Heat Pump Systems in Residential Buildings." *World Geothermal Congress 2015* (April):19–25.

O'Hagan, Anthony. 2004. "Bayesian Statistics: Principles and Benefits." Pp. 31–45 in *Bayesian statistics and quality modelling in agro-food production chain (Wageningen UR Frontis Series)*, edited by V. Boekel and S. A. and van B. A. H. C. MAJS. Kluwer Academic Publishers.

Parent, Éric and Jacques Bernier. 2007. "Le Raisonnement Bayésien Modélisation et Inférence." in *Le raisonnement bayésien: modélisation et inférence*.

Patel, Mr Rajendrakumar, Mr Nilesh Sheth, and Mr kamlesh Patel. 2015. "Energy Conservation Opportunity with a Variable Frequency Drive in Boiler Feed Pump." *International Journal of Application or Innovation in Engineering & Management* 4(2):181–88.

Radgen, Peter and Julia Oberschmidt. 2008. "Fans for Ventilation in Non Residential Buildings Final Report." *Fraunhofer* (April):204.

Reine, Preston and Lead Analyst. 2015. "Low Voltage Motors Report – 2015 Actuals and Forecast :"

Rivalin, Lisa, Benoit Cogné, and Marcello Caciolo. 2013. *Engie Axima Internal Communication : Fan and VFD Efficiencies Estimation, Impact on Energy Performance Contracting*.

Rivalin, Lisa, Pascal Stabat, Dominique Marchio, Marcello Caciolo, and Frédéric Hopquin. 2018. "A Comparison of Methods for Uncertainty and Sensitivity Analysis Applied to the Energy Performance of New Commercial Buildings." *Energy and Buildings* 166:489–504. Retrieved (http://linkinghub.elsevier.com/retrieve/pii/S0378778818305243).

Sfeir, Alain and Michel A. Bernier. 2005. "A Methodology to Evaluate Pumping Energy Consumption in GCHP Systems." 111:1–16.

Simpson, Angus R. and Angela Marchi. 2013. "Evaluating the Approximation of the Affinity Laws and Improving the Efficiency Estimate for Variable Speed Pumps." *Journal of Hydraulic Engineering* 139(12):1314–17. Retrieved (http://ascelibrary.org/doi/10.1061/%28ASCE%29HY.1943-7900.0000776).

Sokol, Julia, Carlos Cerezo Davila, and Christoph F. Reinhart. 2017. "Validation of a Bayesian-Based Method for Defining Residential Archetypes in Urban Building Energy Models." *Energy and Buildings* 134:11–24. Retrieved (http://dx.doi.org/10.1016/j.enbuild.2016.10.050).

Thambidura, Kelvin Mohan and Y. 2013. "Affinity Laws: Interpretations and Applications for Centrifugal Pumps." *Jurutera IEM* (June).

Tian, Wei et al. 2018. "A Review of Uncertainty Analysis in Building Energy Assessment." *Renewable and Sustainable Energy Reviews* 93(May):285–301. Retrieved (https://doi.org/10.1016/j.rser.2018.05.029).

U.S. Department of Energy (DOE) Industrial Technologies Program. 2003. *MotorMaster 4.0 User Guide*.

Vilanova, M. R. N. and J. A. P. Balestieri. 2015. "Modeling of Hydraulic and Energy Efficiency Indicators for Water Supply Systems." *Renewable and Sustainable Energy Reviews* 48:540–57.

Waide, Paul and Conrad U. Brunner. 2011. "Energy-Efficiency Policy Opportunities for Electric Motor-Driven Systems." *International Energy Agency* na(na):132.

Wu, Peng, Zhounian Lai, Dazhuan Wu, and Leqin Wang. 2014. "Optimization Research of Parallel Pump System for Improving Energy Efficiency." *Journal of Water Resources Planning and Management* 141(8):1–8.

Yuan, Jun, Victor Nian, and Bin Su. 2017. “A Meta Model Based Bayesian Approach for Building Energy Models Calibration.” *Energy Procedia* 143:161–66. Retrieved (https://doi.org/10.1016/j.egypro.2017.12.665).