Machine-Learning Based Energy Estimation on a High-Speed Transportation System

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Abstract. Reducing the energy absorption of automatic machines used in industry is one of the main goals towards the reduction of the carbon footprint, as well of the economic cost, of mass-produced goods. Incorporating energy improvements to existing machines and established technological processes can however be challenging, due to the complexity of estimating with a sufficient level of detail the actual energy consumption of a machine and even more by the difficulty of guessing the required modifications that allow to reduce such energy consumption. This work explores the possibility of using machine learning as a tool that allows estimating the energy consumption of a transportation system from a reduced set of numerical data that represent the main feature of the motion profile, in order to develop a model to be used for planning energy-efficient motion profiles. The investigation is based on experimental data gathered for a high-speed transportation device.

Keywords: SDG9 · SDG12 · machine learning · energy consumption · Gaussian Process Regression · energy saving

1 Introduction

Reducing the energy consumption is one of the main challenge that society has to face, owing to the impact of the use of non-renewable resources has on the environment. The area for improvements in this sense is enormous, considering that current trends reveal that global energy demand is expected to grow at a constant rate over the next decades [11], while the concern for the global warming suggests a total and immediate inversion of this trend. Reducing energy consumption in all sectors is of paramount importance for ensuring energy security, sustainability, to reduce emissions and to support job creation [9]. Industry must embrace this challenge by researching and implementing technologies that allow to reduce the amount of energy involved in each process, allowing to 'do more with less energy'. The call to industry for a greener production is clearly outlined in the SDG12 and SDG9: the latter explicitly suggests to 'upgrade

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infrastructure and retrofit industries to make them sustainable with increased resource-use efficiency and greater adoption of clean and environmentally sound technologies and industrial processes'.

Researches have been working on the theoretical and technological issues of measuring, estimating, predicting and finally improving the energy consumption of automatic machines [14] and robots [3,12] for many years. A large part of this research has analysed in the review work [5], which lists almost 100 works published between 1993 and 2018. The improvement of the energy efficiency of an automatic machine can happen at any level of its development, but whenever possible, energy efficiency should be tackled at the design stage [2,10] by choosing the appropriate components, but also focusing on just the design of motion profiles can be a rather effective method to reduce energy consumption without sacrificing productivity [1,4] and with a minimal investment. As a result, large part of the literature on the topic has been focused on investigating the relationship between motion profiles and energy consumption, here just a few notable samples are cited. In the work [7] the authors focus on the analysis of the dominant factor that influence energy consumption in a rest-to-rest motion task, providing some general guidelines for the choice of the best profile among standard ones. The work [6] proposed a radically different approach, in which a trapezoidal motion profile is optimized in real-time to achieve minimum energy consumption with limited residual oscillations. Finally, an analytic approach is proposed in [14], by defining a set of analytic relationship that provide a simple but very effective parametrization of the overall energy consumption for any constant inertia system and for any rest-to-rest motion profile. These work proposed three radically different approaches, but they all are based on a somehow detailed knowledge of the physical parameters of the system, and as such, their accuracy and their practicality strongly depend on the possibility of getting such data. This can be difficult - or even impossible - when the data disclosed by the manufacturer are not sufficiently detailed. In order to overcome this frequent issue, the use of machine learning algorithm is proposed in this work as a feasible alternative to the most common physics-based models to develop energy consumption models, using some data collected on the field and without involving any specific physical parameter of the device under investigation. The latter, in particular, is an high-speed transportation system built by B&R, the ACOPOStrack. The aim of the algorithm is to develop an energy estimation model that relies just on some parameter that characterize the reference motion profile to be executed by the machine, that is sufficiently accurate and robust to enhance the energy efficiency of the device under investigation.

2 Machine Learning: Gaussian Process Regression

The model development procedure proposed here is based on the Gaussian Process Regression (GPR). The latter is a probabilistic supervised machine learning framework [13] that is used to predict continuous quantities. The basic idea of supervised machine learning is to provide to the algorithm some input data, as

Fig. 1. The experimental setup: B&R ACOPOStrack

well as the corresponding outputs, to be used to train the model to be developed. In its most basic implementation, the model is built by fitting a set of data by a non-linear regression form. Unlike a standard non-linear regression, the set of infinite interpolating functions are described, rather than by standard functions, by Gaussian processes. The latter are collections of random variables, any finite number of which have consistent Gaussian distributions. A Gaussian process is uniquely defined by a mean function $m(x)$ and a covariance function $K(x, x')$, so that the model that fits the data collected in x is represented as:

$$y = f(x) \sim \mathcal{GP}(m(x), K(x, x')) \tag{1}$$

The use of Gaussian processes allows to define, in a single object, an infinite set of interpolating function, each one characterized by a mean value and a variance. The method used here, which is based on the software implementation made available by MATLAB, includes also a nonlinear regression term, as in:

$$y = h(x)^T \beta + f(x) \tag{2}$$

At the end of the iteration procedure, which strives at the best possible accuracy in reproducing the input/output relationship, a single model is needed rather than an infinite number of models described by some probability functions: the one with the highest probability is chosen as the one best fitting the model. For a more detailed explanation the reader might refer to the classic book [13]. In most cases then, as is the case for this work, the set of available measurements x is split into two parts, so that some measurements are used to train the deep-learning algorithm, the other ones are instead used to evaluate the fitness of the model.

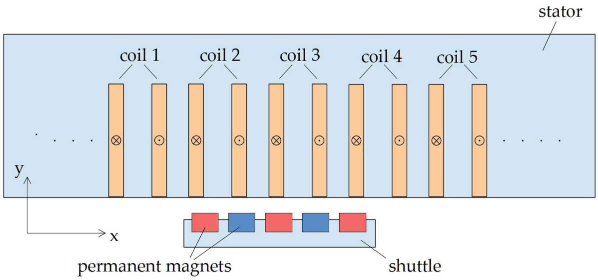

Fig. 2. Stator and shuttle: section view

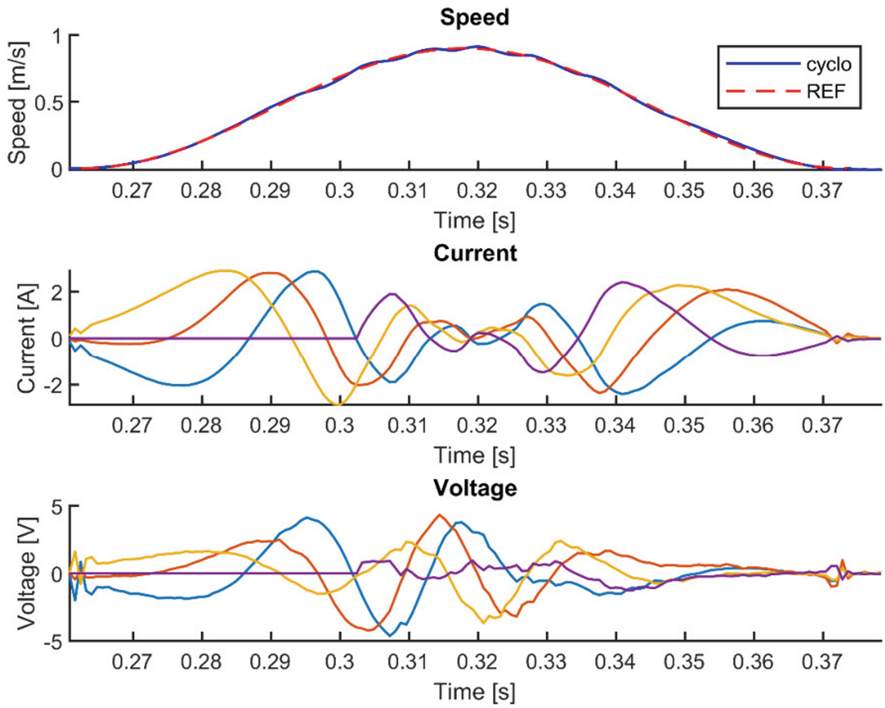

Fig. 3. Measured data: cart speed, phase currents and voltages

3 Experimental Data and Model Fitting

The ACOPOStrack (see Fig. 1) is a transportation system which allows to move one or more shuttles along a sequence of stators, that can be arranged to create 'tracks'. Each shuttle can carry a payload up to 1 kg, and each shuttle can be controlled independently from the others. The structure of each element of the ACOPOStrack resembles the one of a Permanent Magnet Linear Synchronous Motor (PMLSM). Each element of the track is a stator, composed in the case under consideration by 42 coils, while the shuttle comprises 5 permanent magnets in alternate orientations [8], as shown in Fig. 2. When properly excited, the stator coils produce a magnetic field that interacts with the ones of the magnets on the shuttle, therefore exerting some force on it. The shuttle is kept at a fixed distance from the stator by four rollers. The electromechanical modeling of the ACOPOStrack is rather complex, as shown in the very detailed paper [8]. The system is however built by PMSLSMs, which are essentially a linear version of their more common 'circular' counterparts. As such, they share the same working principle and similar modeling features, hence we can refer to the results developed for traditional motors in terms on the estimation of their power consumption. In particular, we might refer to the work of one of the authors [14], in which a detailed analysis of the electric power consumption of a single axis servo-actuated system with constant inertia is carried out. One of the main results of the work is the development of analytic solutions to compute the energy required by a rest-to-rest motion task. In particular, the paper highlights that for a given device (and for a constant payload mass) such an energy consumption is a function of a limited set of variables, namely the total execution time of the motion, T, the overall displacement h, the RMS velocity coefficient, c_{Vrms}, and the RMS acceleration coefficient, c_{Arms}, of the commanded the motion profile. The other parameters involved in the estimation model are some physical parameters, some of which are however hard to estimate with precision, such as friction forces, the torque constant, the winding resistance, or the back-emf constant of the motor, just to cite some of the most relevant ones. The proposed approach solves the issue of providing precise and robust estimations for such parameters, as they are not directly involved in the model tuning procedure operated by the machine learning approach. The development of the model has been conducted by first running a large set of experiments, by moving one shuttle each time according to a different motion profile: the data set used for the experiments whose results are presented here refer to 200 samples of profiles tuned with displacements ranging from $h = 0.05\,\text{m}$ to $h = 0.10\,\text{m}$, with execution times ranging from $T = 0.08\,\text{s}$ to $T = 0.5\,\text{s}$, and using either a cubic or a quintic function to describe the motion profile. The limitation of the displacement, in this preliminary study, is related to the possibility of measuring the information of just four phases. The data collected for each trial includes the position of the shuttle, the voltage and the current of the four stator phases involved in the motion. One example of this kind of measurement is found in Fig. 3.

The voltage-current product for each phase allows then to compute the instantaneous power draw by it, which is then summed over the four coils and integrated over time. Such calculation leads to the estimation of the energy consumption associated with the execution of each motion task, which is displayed in Fig. 4 for the motion of Fig. 3. Half of the 200 samples are used to train the machine learning algorithm, while the other half is used to assess its prediction capabilities. The input to the algorithm include four numeric data: the overall displacement h, the total execution time T, the two RMS coefficients of velocity and acceleration - i.e. the 4 relevant parameters that describe the motion profile. It must be pointed out that the machine learning algorithm does not possess any

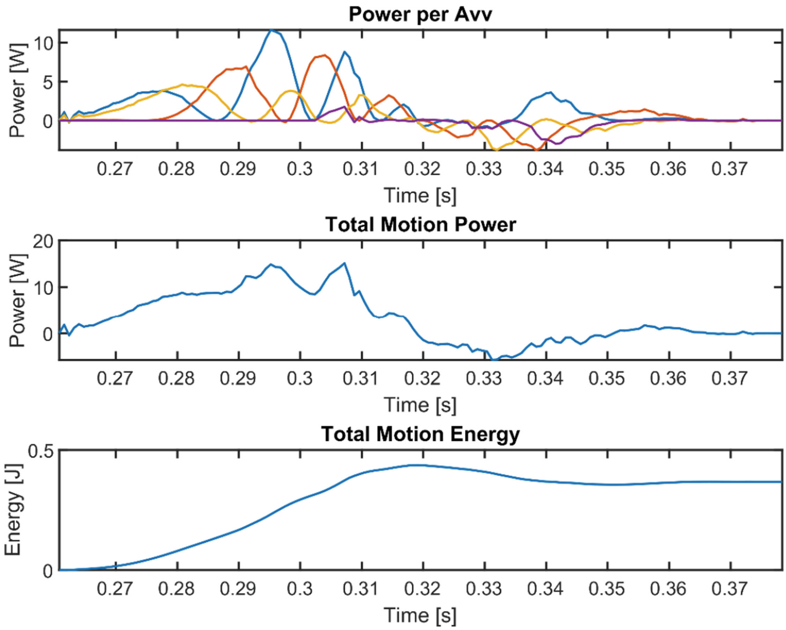

Fig. 4. Measured data: electric power for each coil, total electric power, total absorbed energy

other information. The output of the algorithm is the total energy consumption, E, measured in Joules. The results of the estimation are shown in Fig. 5: the figure shows in the first plot the energy associated with the 100 samples used for the results assessment: the estimated energy data, shown by blue dots, are compared with their values as estimated by the machine learning procedure, which are shown by orange circles. The likeness between the two is then measured by the correlation coefficient R, whose value is found to be equal to $R = 0.9983$: its proximity to one provides a first confirmation of the very good accuracy of the method. The data are then characterized by the Mean Squared Error (MSE), which is found to be equal to 0.0001248 J: the barplot on the bottom left-hand side of the figure shows that for the vast majority of the trials the prediction error is confined within ± 0.02 J. The distribution of the percentage error among all 100 test samples is shown in the last graph: it shows that for 97 among the 100 samples the energy estimation error is with a $\pm 6\%$ range. In all the other three cases the prediction error does not exceed 10%. The overall Mean Absolute Percentage Error (MAPE) is equal to just 1.892%. All these data suggest that the proposed method is very effective in estimating the energy consumption from a limited set of data.

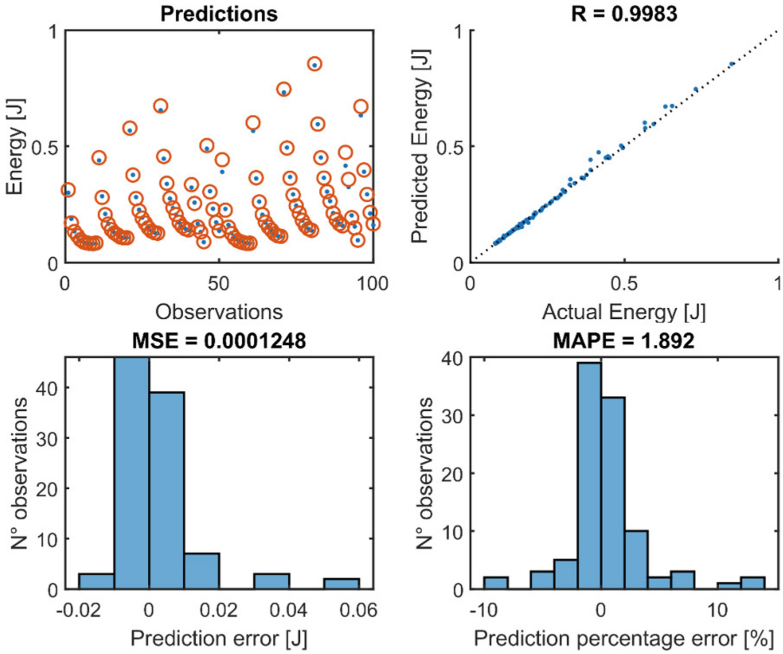

Fig. 5. (a) Comparison of measured and predicted energy consumptions, (b) correlation chart, (c) prediction error distribution by MSE, (d) prediction error distribution by MAPE

4 Conclusion

This work proposes some preliminary results on the possibility of using machine learning methods to estimate the energy consumption of a servo-actuated system with constant inertia. In particular, the Gaussian Process Regression method has been used to develop a model that allows the prediction of the energy consumption of an high speed transportation system when executing a rest-to-rest motion task. The model has been trained using the data collected from a large number of experimental tests conducted by executing several motion profiles, during which the electric energy consumption of the machine has been measured. As a result of the training procedure, the prediction algorithm has proven to be capable of high accuracy whilst relying on just a simple set of parameters for the description of each experiment, namely the overall displacement, its duration, and the RMS coefficient of velocity and acceleration that characterize the motion profile. Machine learning has therefore proved to be a feasible method for energy estimation purposes, which defies the several challenges imposed by a purely physical modeling.

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