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INTELLIGENT MANGEMENT OF ENERGY SYSTEM IN MANUFACTURING PROCESS USING DATA-DRIVEN STOCHASTIC MODEL

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Abstract. *To overcome the environmental impacts of a manufacturing factory over its life cycle, the role of sustainable energy effectiveness is vital. For this reason, implementing energy conservation technologies to empower energy efficiency has become an essential business for most manufacturing plants. Data-driven control setups are a novel idea to handle the energy efficiency of such complex systems, while machine learning is becoming well-known in the system engineering community. In this paper, a new approach together with optimal control application is considered to open promising energy-saving ideas through investigating machines of a factory using machine learning, specifically, Gaussian Processes (GP), where the model is built by correlating the dynamics, complexity, and interrelated energy consumption recordings. We connect the idea with controlling a manufacturing system energy in an optimized way, where the Model Predictive Control loop delivers optimal solutions for each control time step. In the end, a numerical example is demonstrated to give a clear picture of the proposed modelling method's potential.*

Keywords: *gaussian processes, machine learning, model predictive control, stochastic model, sustainable manufacturing.*

I. INTRODUCTION

Improvements in distributing total energy economically optimal are among the major prerequisites to fulfil the demand of industrial process facilities due to high and fluctuating prices in local and global energy markets. Even though many innovative approaches have been discovered and implemented consistently, the energy management requirements have not been fully utilized. Thus, manufacturing facility managers' society still lacks novel ideas to overcome concerns about energy efficiency [1]. Moreover, the role and contribution of continuous reductions in energy consumption over a manufacturing factory's life cycle to cut off GHG emission impact are crucial in jumping towards an eco-friendly environment. For these reasons, identifying energy-related problems have become a hot area of interest in recent years. Herrmann et al. [2]-[3] proposed his state of the art for optimized process chains and locations of technical building services. Devoldere et al. [4]-[5] researched energy-related impact and cost reduction proposals for machine design in the production line. The combinations of power metering with sensors to monitor energy management systems was another considerable work by authors of [6]-[9]. On the other hand, Abdufattokhov et al. [10] tested the performance of the data-driven control idea and showed the proposed technique has a promising future. Our contribution in this work is to solve the aforementioned problem through discussions on how artificial intelligence technics can be applied to data collected from machines in order to achieve energy-efficient manufacturing management using Model Predictive Control (MPC). MPC has been applied to real systems and shown to be an efficient supervisory control solution providing 17 % energy savings with better thermal comfort over rule-based control [11] with the ability to estimate a plant's future response using a statistical model.

The reminder of the paper content is organized as follows: In section II, primary energy consumers and producers in a manufacturing process is explained, followed by an approach on how data can be collected. Next, two sections III and IV are devoted to the methodology of the proposed approach. Finally, we end up with a demonstrative example and conclude sections V and VI, respectively.

II. DATA ACQUISITION FROM MANUFACTURING PROCESS

Total energy delivered to a manufacturing factory is wasted for production and auxiliary services. While the former can include machine tools, conveyors, robots, heaters, fridges, etc., the latter includes chillers, air compressors, boilers, lighting and etc. As shown in Figure 1, the chillers' workload is to negotiate with the heat produced by machines of the production system, taking into account constraint qualifications. In addition, there exist three primary energy emissive sources: heat transferred from ambient environment $Q_{conduction}$, by radiation from sunshine $Q_{radiation}$, and the last one, heat coming from doors or windows openings, $Q_{infiltration}$.

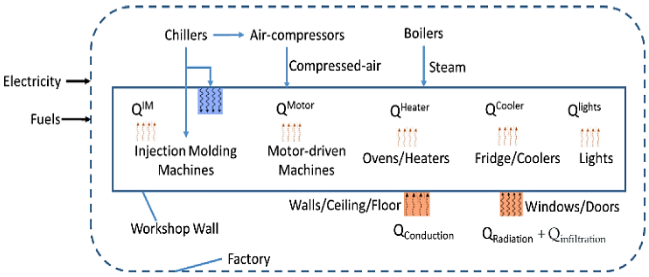

Fig. 1 Energy distribution among main consumers in a factory.

From Figure 1, it is evident that the relationships are complex, non-linear, and dynamic. Although it may seem possible to model theoretically their dynamic correlations based on physical engineering theories with acceptable accuracy for a realistic understanding of their behaviours, in reality, controlling their performance for energy efficiency remains extremely difficult. One possible way to achieve the objectives without relying on theoretical models is to collect energy consumption and operation data and develop a model of the system using the data only. Since our focus is improving energy efficiency, the power consumption **p** is an objective parameter, and it is defined by several output measurements **y**, which can be formulated as a function of control inputs **u**. We can collect time-series data matrix $\mathbf{M_a}$ as follows

$$M^a = |p^a \ \ y^a \ \ u^a| = \begin{cases} p^a = |p_i^a| \\ y^a = |y_{ij}^a| \\ u^a = |u_{ik}^a| \end{cases} \qquad (1)$$

where i=1,2,3…n; j=1,2,3…m; k=1,2,3…q.

a - machine type superscript;

i - time interval, j - th output and k - th input parameter subscripts, respectively;

n - is the total number of data gathered;

m - is the total number of output parameters;

q - is the total number of input parameters.

For example, u_{ik}^{a} stands for the value of input parameter k of machine a at time interval i. Similarly, time-series matrix for energy consumption and operation data of other systems can be obtained through either SCADA(supervisory control and data acquisation) software system or directly from relevant digital sensors.

III. PREDICTIVE MODELLING USING GAUSSIAN PROCESSES

In most deterministic machine learning algorithms, difficulties in the training process stem from a lack of inefficient data. When the model is chosen, examining directions anticipated from this model leave the training data. Although the forecasts of the capacity approximator are discretionary, they are guaranteed with "full certainty" [12]. To conquer the issue, building up a model dependent on an appropriate intelligent algorithm that fabricates the framework's model utilizing a stochastic capacity approximator that puts a back dispersion over the mapping capacity and communicates the degree of vulnerability about the model [11] another option and practical arrangement. Thus, we initially require a probabilistic model to communicate model vulnerability for gaining without any preparation. See Figure 2 for visualizing what is aimed to construct in the paper. Hence, for learning from scratch, we initially need a probabilistic model to express model uncertainty. For this purpose, we can use a non-parametric probabilistic Gaussian Processes Regression(GPR) to prepare a model.

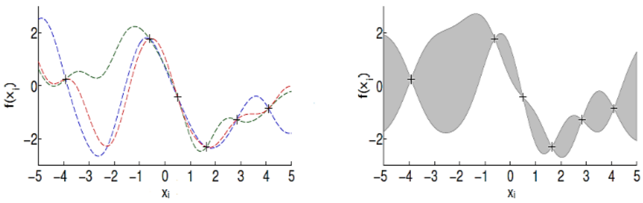

Fig. 2 '+' - training samples. Deterministic function approximators (left) and Probabilistic function approximator (right).

Gaussian Processes Regression

A Gaussian processes is a batch of random variables, which form Gaussian distribution jointly. We can include the Gaussian Processes(GP) models into a class of a nonparametric method of nonlinear system identification where new predictions of system behaviour are computed through the use of Bayesian inference techniques applied to empirical data [11]. GP models can be considered as a new approache such as Support Vector Machines [13]-[14]. In addition, GPs make possibile to include various kinds of prior knowledge into the model [15] for the incorporation of local models and the static characteristic.

A GPs is completely specified by its mean function and covariance function. It is very common to define mean function $m_f(x)$ and the covariance function $C_f(x_i, x_j)$ of a dynamic process *f(x)* under consideration as

$$m_f(x_i) = E[f(x_i)] \quad (2)$$

$$C_f(x_i, x_j) = E\left[\left(f(x_i) - m_f(x_i)\right)\left(f(x_j) - m_f(x_j)\right)\right] \quad (3)$$

In order to develop a prognostic model using predefined data in Section II, we use GPs, please refer to [1] for more brief details.

Consider the system

$$y = f(x) + \epsilon \qquad (4)$$

with the white Gaussian noise $\epsilon \sim N(0, \sigma_n^2)$, with the variance σ_n^2 and the vector of regressors x from the input dimension space R^D. We have $[y_1 \ldots y_n]^T \sim N(0,K)$ with

$$K = K_f + \sigma_n^2 I \qquad (5)$$

where K_f is the covariance matrix for the noise-free f of the system that is evaluated from the covariance function $C_f(x_i, x_j)$ applied to all the pairs i and j of measured data. I is the n x n identity matrix. More information on a wide range of mean and covariance functions together with its use in GP models can be found in [16]. Here, we consider the composite covariance function made out of the squared exponential covariance function and the constant covariance function because of uncertainties caused by environment:

$$C(x_i, x_j) = \sigma_f^2 \exp\left[-\frac{1}{2}\sum_{d=1}^{D}\theta_d(x_i^d - x_i^d)\right] + \sigma_n^2 \delta_{ij} \qquad (6)$$

Prediction with Gaussian Processes Regression

In order to predict a new output estimate y^* of the GP model for a given x^*, we use Bayesian framework [19]. The following step is to find how a new input is inserted to the covariance matrix K_{n+1}. For the batch of random variables $[y_1 \ldots y_n, y^*]$ we define:

$$Y_{n+1} \sim N(0, K_{n+1}) \qquad (7)$$

with the covariance matrix

$$K_{n+1} = \begin{pmatrix} K & K_* \\ K_*^T & K_{**} \end{pmatrix} \qquad (8)$$

where

$K_* = [C(x_1, x^*), \ldots, C(x_n, x^*)]$ is the nx1 vector of covariances between the training and the test input data,

$K_{**} = C(x^*, x^*)$ is the autocovariance submatrix of the test input data.

Finally, we end up with the Gaussian prediction with the following mean and variance:

$$E[y^*] = \mu(x^*) = m_f(x^*) + K_*^T K^{-1}\left(Y - m_f(X)\right) \qquad (9)$$
$$var[y^*] = \sigma^2(x^*) = K_{**} - K_*^T K^{-1} K_* \qquad (10)$$

IV. GPR BASED MODEL PREDICTIVE CONTROL

Introduction to MPC

Model Predictive Control (MPC) is one member of the most popular and widely spreaded control algorithms that the future plant response is predicted using an explicit process model in industrial use. Thanks to a trustful and robust predicted system output and prediction control horizon, the MPC algorithm optimises the controllable variables to use an optimal future plant response for the next several steps. The prediction horizon range together with optimisation ability of MPC algorithms to handle with constraints that are often met in control practice have made it popular and widely used compared to other approaches in many applications [20]-[24].

The MPC working standard can be summed up as follows:

1. Expectation of framework yield signal $y(\tau + h)$ is determined for each discrete example τ for future $h = 1,2 \dots N_h$. Estimations are meant as $\bar{y}(\tau + h|\tau)$ and defines h - step ahead estimation, while N_h is an upper bound of forecast horizon. Yield signal forecast is determined from our GP procedure model. Estimations are reliant on the control situation later on $u(\tau + h|\tau)$; $h = 1,2 \dots N_h - 1$, which is applied from a second τ onwards.

2. The vector of future control signals $u(\tau + h|\tau)$; $h = 1,2 \dots N_h - 1$ is determined by minimization of estimation error $\bar{y}(\tau + h|\tau)$.

3. Just the principal component of the optimal control signal vector is applied. In the following emphasis, another deliberate yield test is recorded and the entire portrayed procedure above is circled inside the loop.

Data-driven control

Combining input-output model of dynamic system with our GP model, we write our dynamical system as follows

$$p(\tau) = f\big(x(\tau)\big) + \epsilon(\tau) \qquad (11)$$

$$x(\tau) = [p(\tau - l_1), \dots, p(\tau - 1), u(\tau - l_2), \dots, u(\tau),\ d(\tau - l_3), \dots, d(\tau)] \qquad (12)$$

with $f \sim GP(\mu_f, \sigma_f^2)$, τ - the time step, ϵ - measurement noise, p - the (past) output, u - the control input, d - the exogenous disturbance input and l_1, l_2, l_3 - the lags for autoregressive outputs, control inputs, and disturbances, respectively.

Optimization problem

Now let's focus on our MPC optimization problem. Since, in our case the process model is GP, including uncertainity term makes possible to design a robust controller that will optimise action according to the validity of model. Overall, the optimization problem with quadratic cost is

$$\min \quad \sum_{h=0}^{N_h} \|\hat{p}^s(\tau + h)\|_Q^2 + \hat{\sigma}^{s2}(\tau + h) + \|u^s(\tau + h)\|_R^2$$

$$\text{s.t. } \hat{p}^s(\tau + h) = m_f^s\big(x^s(\tau + h)\big) + K_*^s K_S^{-1}\Big(Y - m_f^s(x^s)\Big)$$

$$\hat{\sigma}^{s2}(\tau + h) = K_{**}^s - K_*^s K_S^{-1} K_*^{sT}$$

$$\hat{p}^s(\tau + h) \in P^s$$

$$u^s(\tau + h) \in U^s$$

(13)

where s stands for machines $a, b, c, \dots$; P^S is state output constraint set, U^s is set of feasible solutions; $\|x\|_A^2 = x^T A x$ Euclidian norm for $x \in R^n$ and Q, R are positive definite matrices.

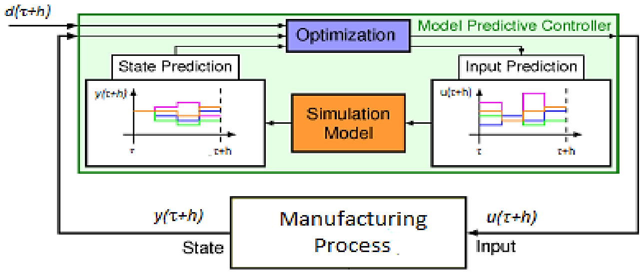

Fig. 3 Structure of GP based MPC. Optimization problem in (10) is solved in every τ time step. Here, u -optimized control input vector applied to machines, d - external disturbance vector and y - output vector measured from machines.

Minimizing terms mentioned above are common ones when working with GP model based dynamical systems and are non-unique. It can be chosen freely depending on the desire and constraints. In Figure 3 one can see overall MPC loop structure together with manufacturing process whose energy usage is controlled through GP model with the data provided by sensors set up on machines.

V. NUMERICAL EXAMPLE

Due to complexity and being time consuming of data collection from manufacturing process, we omit illustration GP based MPC on real industrial system. Rather, the accompanying state space model below (11) outlines the utilization of proposed GP strategy for system identification of highly fluctuating and non-periodic system. Simulation were carried out in Matlab software and CPU Intel Core i5-5200U.

Consider the following discrete nonlinear system:

$$\begin{cases} y_1(\tau+1) = y_1(\tau) + \sin\big(y_1(\tau)\big) + \frac{1}{2}\big(u_1(\tau) + u_3(\tau)\big) + \nu(\tau) \\ y_2(\tau+1) = y_2(\tau) + \frac{4}{5}\cos\big(y_1(\tau)\big) + \frac{3}{5}u_1(\tau) - u_2(\tau) \\ p(\tau) = y_2(\tau) + w(\tau) \end{cases} \quad (14)$$

The yield of the given model is output p (can be looked as machine power) that is disrupted with Gaussian white noise with $\nu \sim \mathrm{N}(0,0.002)$, whereas state y_1 is suffered by noise $w \sim \mathrm{N}(0,0.0035)$ We generate 3 inputs by a random number generator with uniform distribution in the magnitude between 10 and 20 for the first input, between 5 and 10 for the second input, and in range 0 and 1 for the last input with number of samples $\mathrm{N} = 600$ by not changing control signals u_1 consecutive 4 time instants, u_2 consecutive 6 time instants and u_3 consecutive 8 time instants. Here, our task is to obtain a GP model for given inputs of the discrete-time system described by (11) based on statistical data and by following step by step the proposed methodology in the section III. We use 66 % of the generated data set N (the rest is used for testing), and the system is modeled by Gaussian Process Regression with zero mean and the covariance function, which is composed of sum of squared exponential and periodic covariance functions. We tried several composite covariance functions, but this one performed with better accuracy.

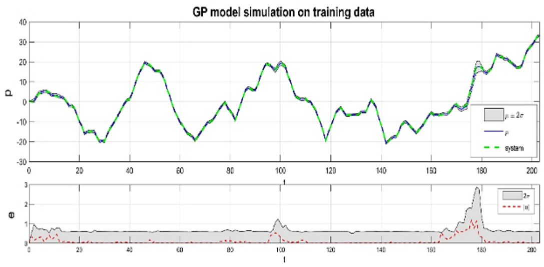

Fig. 4 GP model performance for the training signal. Upper part plots the true values, the predicted mean and 95 % confidence intervals, whereas below part shows the absolute residuals.

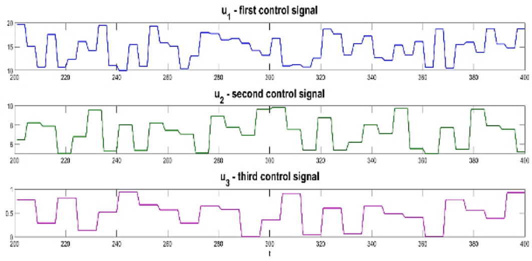

Fig. 5 Control signals of training data

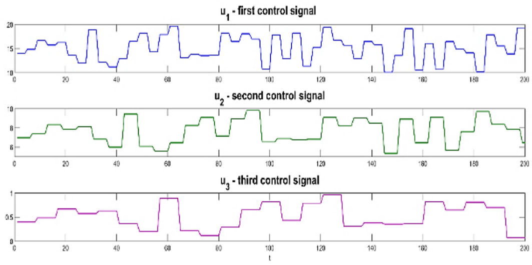

Fig. 6 Control signals of test data

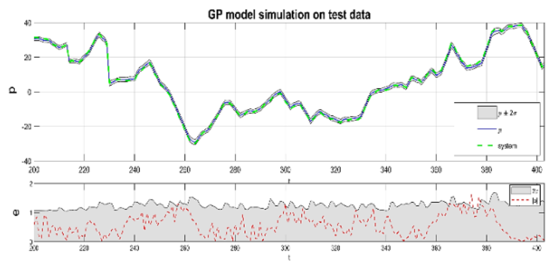

Fig. 7 GP model performance for the test signal. Upper part plots the true values, the predicted meanand 95 % confidence intervals, whereas below part shows the absolute residuals

Models of various orders were fitted as highlighted in Table 1 , as a result our proposed approach found the second order model with $l_p = 2$, $l_{u_1} = 1$, $l_{u_2} = 1$, $l_{u_3} = 1$, and $l_d = 0$ as the most appropriate with metrics NRMSE=0.00950 and MSLL=-3.1754 provided in [20]. The results of the Gaussian Processes model to the training and test signals are given in Figure 4 and Figure 7, respectively. One can see that, even though test data fitting graph has larger variance, it still captures the trajectory well. On the other hand, Figure 5 and Figure 6 illustrates control signals applied to the system during model identification, where we can see not repeated line graphs, values are different for each control signal in both phases. Furthermore, it is remarkable that the system is depend on control signals at the previous time step, because in absence of controller signal, the accuracy experienced a significant decrease Table 1.

Table 1. GPR modeling accuracy results for test data.

MODEL ORDER	NRMSE	MSLL
$l_p = 3, l_{u_1} = 2,\ l_{u_2} = 2, l_{u_3} = 2, l_d = 1$	0.15098	-1.02915
$l_p = 2, l_{u_1} = 1,\ l_{u_2} = 1, l_{u_3} = 1, l_d = 0$	0.00950	-3.1754
$l_p = 2, l_{u_1} = 1,\ l_{u_2} = 2,\ l_{u_3} = 1, l_d = 0$	0.01844	-2.09245
$l_p = 2, l_{u_1} = 0,\ l_{u_2} = 1, l_{u_3} = 1, l_d = 0$	0.11951	1.08813

VI. CONCLUSIONS

This paper tried to show how dynamic systems can be modelled using machine learning. Specifically, Gaussian Processes Regression is applied to historical data collected from sensors of production machines. Once we have defined the modelling sequence, we connected the idea with the possibility to use this algorithm in controlling the manufacturing system in an optimized way, where the Model Predictive Control loop defines optimal solutions for each control time step. In the end, the numerical example presented GPR modelling potentials. The proposed approach can be looked at as a new tool for identifying energy-saving perspectives and quantifying their respective energy-saving potentials.

Moreover, it provides a trust region with 95 % confidence that enables the discovery of unseen energy-saving challenges that seem hard to identify. In particular, this can be a fundamental idea for companies with successful energy improvement programs to empower their research areas for further improvement. Our next mission will be to show the interpretability and advantages of the proposed method through experimental results based on data of real system dynamics.

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