Barqaror energiyani boshqarish uchun ishlab chiqarish tizimlarini ma'lumotlarga asoslangan stokastik modellashtirish

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Dolzarblik: ishning dolazarbligi elektr energiyasi iste'molini prognozlash aniqligini oshirish va buning natijasida barqaror energiya samaradorligi orqali ishlab chiqarish zavodlarining atrof-muhitga ta'sirini kamaytirish hisoblanadi. Bu energiya tejamkorligiga erishishda energiya tejash texnologiyalarining ahamiyatini ta'kidlaydi va murakkab tizimlarda energiya sarfini optimallashtirish uchun yangi, ma'lumotlarga asoslangan boshqaruv sozlamalarini taqdim etadi. Tadqiqot, ayniqsa, tizim muhandisligi hamjamiyatiga taalluqlidir, chunki u ishlab chiqarish tizimlarida energiya sarfini modellashtirish va boshqarish uchun mashinani o'rganishdan, xususan Gauss jarayonlaridan foydalanishni o'rganadi. Ishlab chiqarish korxonalarida elektr energiyasi iste'molini prognozlash ko'rsatkichlarini aniqlashda, zamonaviy yuqori aniqlikdagi prognozlash usullaridan foydalanish muhim ahamiyatga ega.

Maqsad: mashinani o'rganish, xususan Gauss jarayonlari regressiyasi (GPR) yordamida ishlab chiqarish tizimlarida energiya samaradorligini oshirish uchun yangi yondashuvni ishlab chiqish va namoyish etish. Tadqiqot ishlab chiqarish mashinalarining dinamikasi, murakkabligi va o'zaro bog'liq energiya iste'moli yozuvlarini o'zaro bog'lashga va optimallashtirilgan energiya tejaydigan echimlarga erishish uchun ushbu modelni Model bashoratli boshqarish (MPC) doirasida qo'llashga intiladi.

Usullar: ishlab chiqarish mashinalaridan to'plangan tarixiy sensor ma'lumotlari asosida Gauss jarayonlari regressiyasidan foydalangan holda model yaratish. Ushbu model mashinalarning dinamikasi va energiya sarfini aks ettiradi. Keyin GPR modeli har bir nazorat vaqtida energiya sarfini minimallashtiradigan optimal boshqaruv harakatlarini yaratish uchun model bashoratli boshqaruv tsikliga birlashtiriladi. Tavsiya etilgan usulning samaradorligini namoyish etish uchun raqamli misol keltirilgan.

Natijalar: GPR ga asoslangan modellashtirish yondashuvi energiya tejash imkoniyatlarini aniqlash va ularning imkoniyatlarini aniqlashda samarali hisoblanadi. Model ishonch mintaqasini 95% ishonch bilan ta'minlaydi, bu esa ilgari ko'rilmagan energiya tejaydigan muammolarni aniqlashga imkon beradi. Tadqiqot shuni ko'rsatadiki, ushbu yondashuv energiya samaradorligini yanada oshirish uchun yangi istiqbolni taklif qilib, energiyani takomillashtirish dasturlari o'rnatilgan kompaniyalar uchun qimmatli vosita bo'lib xizmat qilishi mumkin.

Kalit so'zlari: Gauss jarayonlari, mashinani o'rganish, modelni bashoratli boshqarish, stoxastik model, barqaror ishlab chiqarish.

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Стохастическое моделирование производственных систем на основе данных для устойчивого управления энергетикой

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Актуальность: вопрос снижение воздействия производственных предприятий на окружающую среду за счет устойчивого повышения энергоэффективности является важнейшим. Этим подчеркивается важность технологий энергосбережения для достижения энергоэффективности и представлена новая система управления, основанная на данных для оптимизации энергопотребления в сложных системах. Это исследование особенно актуально для сообщества системных инженеров, поскольку оно исследует использование машинного обучения, в частности гауссовских процессов, для моделирования и контроля энергопотребления в производственных системах.

Цель: разработать и продемонстрировать новый подход к повышению энергоэффективности производственных систем с использованием машинного обучения, в частности, регрессии гауссовых процессов (GPR). Цель исследования - сопоставить динамику, сложность и взаимосвязанные показатели энергопотребления производственных машин и применить эту модель в рамках модели прогнозирующего управления (MPC) для достижения оптимизированных решений по энергосбережению.

Методы: построение модели с использованием регрессии гауссовых процессов на основе ретроспективных данных датчиков, собранных с производственных машин. Эта модель отражает

динамику и структуру энергопотребления машин. Затем георадарная модель интегрируется в модельный прогнозирующий контур управления для выработки оптимальных управляющих воздействий, которые минимизируют потребление энергии на каждом временном шаге управления. Для демонстрации эффективности предложенного метода приводится числовой пример.
Результаты: предлагаемый подход к моделированию на основе георадара эффективен при выявлении возможностей энергосбережения и количественной оценке их потенциала. Модель предоставляет область доверия с 95%-ной достоверностью, что позволяет выявить не решаемые ранее проблемы в области энергосбережения. Исследование показывает, что этот подход может послужить ценным инструментом для компаний с установленными программами повышения энергоэффективности, предлагая новые перспективы для её дальнейшего повышения.
Ключевые слова: Гауссовские процессы, машинное обучение, модель прогнозирующего управления, стохастическая модель, устойчивое производство.

Data-driven stochastic modelling of manufacturing systems for sustainable energy management

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Relevance: the critical issue of reducing the environmental impact of manufacturing factories through sustainable energy efficiency. It emphasizes the importance of energy conservation technologies in achieving energy efficiency and introduces a novel, data-driven control setup for optimizing energy consumption in complex systems. The study is particularly relevant to the system engineering community as it explores the use of machine learning, specifically Gaussian Processes, to model and control energy consumption in manufacturing systems.
Aim: to develop and demonstrate a new approach for enhancing energy efficiency in manufacturing systems by using machine learning, specifically Gaussian Processes Regression (GPR). The study seeks to correlate the dynamics, complexity, and interrelated energy consumption recordings of production machines and apply this model within a Model Predictive Control (MPC) framework to achieve optimized energy-saving solutions.
Methods: building a model using Gaussian Processes Regression based on historical sensor data collected from production machines. This model captures the dynamics and energy consumption patterns of the machines. The GPR model is then integrated into a Model Predictive Control loop to generate optimal control actions that minimize energy consumption at each control time step. A numerical example is provided to demonstrate the effectiveness of the proposed method.
Results: the proposed GPR-based modelling approach is effective in identifying energy-saving opportunities and quantifying their potential. The model provides a trust region with 95% confidence, allowing for the identification of previously unseen energy-saving challenges. The study suggests that this approach can serve as a valuable tool for companies with established energy improvement programs, offering a new perspective for further enhancement of energy efficiency.
Keywords: Gaussian processes, machine learning, model predictive control, stochastic model, sustainable manufacturing.

1. 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]-[2]. 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 has become a hot area of interest in recent years. Herrmann et al. [3] proposed. his state of the art for optimized process chains and locations of technical building services. Devoldere et al. [4] 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 [5]-[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 problem through discussions on how artificial intelligence technics can be applied to data collected from machines 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 using rule-based control [11] with the ability to estimate a plant's future response using a statistical model.

2. Materials and Methods

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 etc. The chillers' workload is to negotiate with the heat produced by machines of the production system, considering constraint qualifications. In addition, there exist three primary energy emissive sources: heat transferred from ambient environment Q_c, by radiation from sunshine Q_r, and the last one, heat coming from doors or windows openings, Q_i. It is evident that the relationships energy distribution among main consumers in a factory 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 behaviors, 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 M^a as follows:

$$M^a = |p^a \ \ y^a \ \ u^a| = \begin{cases} p^a = \ |p_i^a| \\ y^a = \ |y_{ij}^a| \\ u^a = \ |u_{ik}^a| \end{cases} \quad ; \tag{1}$$

where $i=1,2,3 \ldots n$, $j=1,2,3 \ldots m$, $k=1,2,3 \ldots q$, 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 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 acquisition) software system or directly from relevant digital sensors.

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 leaves the training data. Although the forecasts of the capacity approximator are discretionary, they are guaranteed with "full certainty". 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 another option and practical arrangement. 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.

The 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 behavior are computed using Bayesian inference techniques applied to empirical data [11]. GP models can be considered as a new approach such as Support Vector Machines [13]. In addition, GPs make it possible to include various kinds of prior knowledge into the model [14] 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:

$$m_f(x_i) = E[f(x_i)] \ ; \tag{2}$$

$$C_f(x_i, x_j) = E\left[\left(f(x_i) - m_f(x_i)\right)\left(f(x_j) - m_f(x_j)\right)\right] \ ; \tag{3}$$

To develop a prognostic model, we use GPs, please refer to [1] for more brief details.

Consider the system:

$$y = f(x) + \ \epsilon, \tag{4}$$

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:

$$K = \ K_f + \ \sigma_n^2 I \ ; \tag{5}$$

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 [15]. Here, we consider the composite covariance function made from the squared exponential covariance function and the constant covariance function because of uncertainties caused by environment:

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

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:

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

with the covariance matrix:

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

where $K_* = [C(x_1, x^*), \ldots, C(x_n, x^*)]$ is the *n x 1* 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:

$$E[y^*] = \mu(x^*) = m_f(x^*) + K_*^T K^{-1}\left(Y - m_f(X)\right); \quad (9)$$

$$var[y^*] = \sigma^2(x^*) = K_{**} - K_*^T K^{-1} K_* \quad (10)$$

Model Predictive Control (MPC) is one member of the most popular and widely spread 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 optimizes the controllable variables to use an optimal future plant response for the next several steps. The prediction horizon range together with optimization ability of MPC algorithms to handle constraints that are often met in control practice have made it popular and widely used compared to other approaches in many applications [16]-[20].

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 $h = 1,2 \ldots N_h$. 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 $u(\tau + h|\tau)$; $h = 1,2 \ldots N_h - 1$, which is applied from a second τ onwards.

2. The vector of future control signals $u(\tau + h|\tau)$; $h = 1,2 \ldots N_h - 1$ 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.

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

$$p(\tau) = f\left(x(\tau)\right) + \epsilon(\tau) ; \quad (11)$$

$$x(\tau) = [p(\tau - l_1), \ldots, p(\tau - 1), u(\tau - l_2), \ldots, u(\tau),\ d(\tau - l_3), \ldots, d(\tau)] ; \quad (12)$$

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.

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

$$\begin{aligned} \text{minimize} \quad & \sum_{h=0}^{N_h} \|\hat{p}^s(\tau + h)\|_Q^2 + \hat{\sigma}^{s2}(\tau + h) + \|u^s(\tau + h)\|_R^2 ; \\ \text{subject to} \quad & \hat{p}^s(\tau + h) = m_f^s\left(x^s(\tau + h)\right) + K_*^s K_S^{-1}\left(Y - m_f^s(x^s)\right) \\ & \hat{\sigma}^{s2}(\tau + h) = K_{**}^s - K_*^s K_S^{-1} K_*^{sT} \quad ; \\ & \hat{p}^s(\tau + h) \in P^s \quad ; \\ & u^s(\tau + h) \in U^s \quad ; \end{aligned} \quad (13)$$

where s stands for machines $a, b, c, \ldots$; 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.

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 1 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.

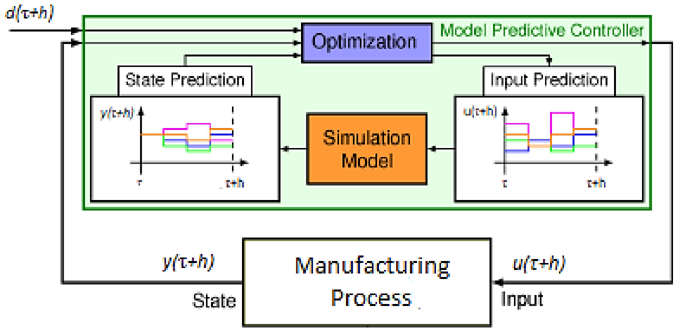

Fig.1. Structure of GP based MPC. Optimization problem in (10) is solved in every τ time step. Here, u - optimized control input vector applied to machines, d - external disturbance vector and y - output vector measured from machines

3. Results

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:

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

The yield of the given model is output p (can be looked as machine power) that is disrupted with Gaussian white noise with $\nu \sim N(0{,}0.002)$, 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. 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.

4. Discussion

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 GP model to the training and test signals are given in Figure 2 and Figure 3, respectively.

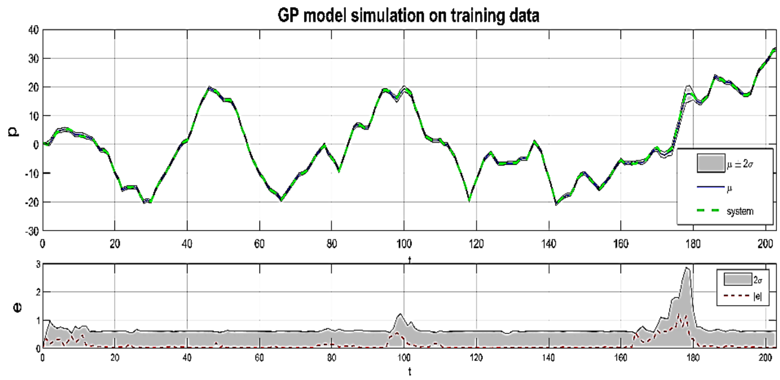

Fig.2. GP model performance for the training signal. The upper part plots the true values, the predicted mean and 95 % confidence intervals, whereas the lower part shows the absolute residuals

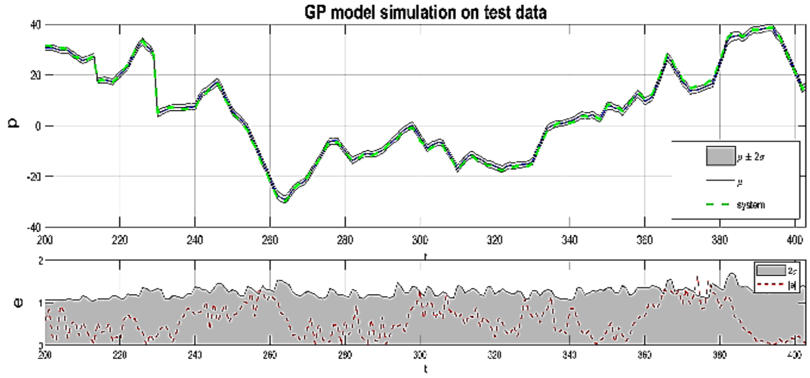

Fig.3. GP model performance for the test signal. The upper part plots the true values, the predicted mean and 95 % confidence intervals, whereas the lower part shows the absolute residuals

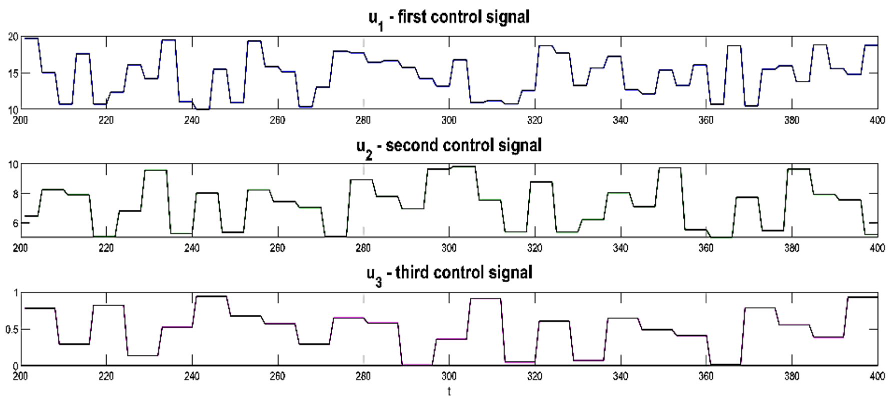

Fig. 4. Control signals of training data

One can see that, even though test data fitting graph has larger variance, it still captures the trajectory well. On the other hand, Figure 4 illustrates control signals applied to the system during model identification, where we can see non-repeated line graphs, values are different for each control signal in both phases. Furthermore, it is remarkable that the system is dependent 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

5. 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. 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.

REFERENCES

1. Abdufattokhov Sh., Muhiddinov B., Stochastic Approach for System Identification using Machine Learning. International Conference on Dynamics of Systems, Mechanisms and Machines (Dynamics). Omsk, IEEE proceedings, 2019.
2. A. Dhankhar, and K. Solanki. A comprehensive review of tools and techniques for big data analysis. International Journal of Emerging Trends in Engineering Research, Vol. 7, no. 11, pp. 556-562, 2019.
3. Herrmann C, Thiede S. Process chain simulation to foster energy efficiency in manufacturing. CIRP Journal of Manufacturing Science and Technology. Vol. 1, no. 4, pp. 221-229, 2009, https://doi.org/10.1016/j.cirpj.2009.06.005.
4. Hesselbach J, Herrmann C, Detzer R, Martin L, Thiede S, Lüdemann B. Energy Efficiency through optimized coordination of production and technical building services. 15th CIRP International Conference on Life Cycle Engineering, 17-19 March, 2008.
5. Devoldere T, Dewulf W, Deprez W, Willems B, Duflou JR. Improvement Potential for Energy Consumption in Discrete Part Production Machines. 15th CIRP International Conference on Life Cycle Engineering, 2007, https://doi.org/10.1007/978-1-84628-935-4_54.
6. Herrmann C, Bogdanski G, Zein A. Industrial Smart Metering–Application of Information Technology Systems to Improve Energy Efficiency in Manufacturing, 43rd CIRP International Conference on Manufacturing Systems, 2010.
7. Bauerdick C JH, Helfert M, Menz B, Abele E. A Common Software Framework for Energy Data Based Monitoring and Controlling for Machine Power Peak Reduction and Workpiece Quality Improvements, Procedia CIRP, Vol. 61, pp. 359-364, 2017, https://doi: 10.1016/j.procir.2016.11.226.
8. S. Abdufattokhov, K. Ibragimova, M. Khaydarova, A. Abdurakhmanov, Data-Driven Finite Horizon Control Based on Gaussian Processes and Its Application To Building Climate Control. International Journal on Technical and Physical Problems of Engineering (IJTPE), Vol. 13, no. 2, pp. 40-47, 2021.
9. David Sturzenegger, Dimitrios Gyalistras, Manfred Morari, and Roy Smith. Model predictive climate control of a swiss office building: Implementation, results, and cost–benefit analysis. IEEE Transactions on Control Systems Technology, Vol. 24, no. 1, pp. 1-12, 2016, https://doi: 10.1109/TCST.2015.2415411.
10. Abdufattokhov Sh., Muhiddinov B., Probabilistic Approach for System Identification using Machine Learning, International Conference on Information Science and Communications Technologies (ICISCT), IEEE proceedings, 2019, https://doi: 10.1109/ICISCT47635.2019.9012025.
11. D. A. Petrosov, R. A. Vashchenko, A. A. Stepovoi, and N. V. Petrosova. Application of artificial neural networks in genetic algorithm control problems, International Journal of Emerging Trends in Engineering Research, Vol. 8, no. 1, pp. 177-181, 2020.
12. Galiana, F., Handschin, E., and Fiechter, A. Identification of stochastic electric load models from physical data. Automatic Control, IEEE Transactions. Vol. 19, no. 6, pp. 887-893, 1974, https://doi: 10.1109/TAC.1974.1100724.
13. Dong, B., Cao, C., and Lee, S. E. Applying support vector machines to predict building energy consumption in tropical region. Energy and Buildings, Vol. 37, no. 5, pp. 545-553, 2005, https://doi.org/10.1016/j.enbuild.2004.09.009.
14. Quinonero-Candela, J., C.E. Rasmussen. Analysis of Some Methods for Reduced Rank Gaussian Process Regression. Lecture Notes in Computer Science, Vol. 1, p. 33-55, 2005.

15. Rasmussen, C. E. and Williams, C. K. I., Gaussian processes for machine learning, Vol. 1, MIT press, Cambridge, MA, 2006.

16. Jus Kocijan., Modelling and control of dynamic systems using Gaussian process models, Springer, 2016.

17. B. Kouvaritakis, M. Cannon, P. Couchman. MPC as a tool for sustainable development integrated policy assessment. IEEE Trans. Autom. Control, Vol. 51, no. 1, pp. 145-149, 2006, https://DOI: 10.1109/TAC.2005.861702.

18. Goffman I.V. Rationing of energy consumption and energy balances of industrial enterprises. Moscow, Energiya Publ., 1966. 319 p. (In Russ.).

19. Dzhedzhula V., Yepifanova I. Optimization of energy saving potential of industrial enterprises. 11th International Conference on Advanced Computer Information Technologies (ACIT), 2021. pp. 433–436. DOI: 10.1109/ACIT52158.2021.9548428.

20. Zhonghai Ch., Meifen X., Quanda Z., Abdufattokhov Sh. Electrical Automation Intelligent Control System Based on Internet of Things Technology. Electrica, Vol. 23, no. 2, 2023.