Artificial intelligence to improve process control from an energy efficiency perspective: A review

Mohamed El Koujok [1], Mouloud Amazouz

CanmetENERGY-Natural Resources Canada, 1615 Boulevard Lionel-Boulet, Varennes, Québec J3X 1P7, Canada

Abstract

This paper presents an overview of how existing control systems can be boosted by artificial intelligence techniques (AITs) to improve energy efficiency and productivity of industrial processes. Control systems are among the pillars for optimal energy management in industrial sectors like pulp and paper, chemicals, oil and gas, and mining. However, these control systems need to be maintained and regularly tuned. These tasks are time consuming and challenging for control engineers. AITs have recently shown their potential in a wide variety of applications involving computer science for process optimization and control. Therefore, this work consists of a critical review of recent academic research publications that have proposed data-driven methods and AITs to monitor and diagnose the deterioration of control system performance. Also, this paper includes a review of some recent works that have proposed a combination of data analytics, digital twins, and other AITs as an effective solution to automate the tuning toward effective control systems. While this paper focuses mainly on how existing control systems can be improved with AITs, it also discusses the application of AITs as next-generation controllers.

Keywords

Energy efficiency, Industrial processes, Artificial intelligence techniques, Process control.

Introduction

The concern for energy efficiency in industrial processes (pulp and paper, chemicals, oil and gas, mining, etc.) has increased over the past few decades. Although management of energy is often a major part of the process operation, plant managers used to focus more on profitability and safety. Recently and after environmental laws have evolved towards a more severe penalty on carbon dioxide emissions (Sutherland (2019)), the optimization of energy use in industrial processes is a matter of absolute necessity. Increasing energy efficiency can be achieved in a variety of ways, starting with the most costly, namely upgrading and adopting new technologies down to the optimization of operations based on operator knowledge. Among these solutions, there are also process control strategies improvement. Properly operating modern industrial processes can not be possible without controllers. Therefore, in typical industrial process, the number of control loops can vary from several hundred to many thousands (Starr et al. (2016)). The control systems aim to automate the industrial operations to achieve desired product quality while making benefit and guaranteeing safety. Controllers are able to minimize the variability that can affect the quality of the product, and indirectly the energy consumption is reduced because the off-spec product is decreased. Besides that, advanced process control systems have the ability to optimize energy use by including it directly in the control strategy as an objective or one of the objectives. Control systems in industrial processes are very complex, and according to Görner et al. (2020), only 10 percent of them are operational or fully exploited. Therefore, getting the most value out of control systems will have a positive impact on achieving optimal energy consumption. Recently, with the rise of Industry 4.0, the emergence of Industrial Internet of Things (IIOT) technologies, and the successful deployment of artificial intelligence (AI) in autonomous cars, the question of controlling industrial processes through AI techniques (AITs) has arisen, and it has been inspired by the progress made in autonomous cars to realize self-driving processes (Gamer et al. (2020)). However, the achievement of fully autonomous industrial processes based just on AITs as the main control technology is very challenging due to the complexity of industrial processes that combine several units operations. A unit operation involves a combination that includes thermodynamic, mechanical, chemical, and electrical mechanisms. Despite the importance of controlling plants using only AITs, it is crucial to begin this particular challenge by exploring: how can AITs be deployed to improve existing and conventional control systems? Accordingly, this work aims to answer this question. First, the ability of AITs to monitor the performance of existing control loops is reviewed and an approach to integrate AITs into control performance assessment (CPA) tools is suggested (Sec. 2). Next, the potential of AITs to in-

[1] Corresponding author: Mohamed El Koujok (E-mail: mohamed.elkoujok@nrcan-rncan.gc.ca).

crease the automation of the tuning of existing control loops is investigated (Sec. 3). The future generation of controllers is discussed in Sec. 4 and a conclusion is included to summarize this work (Sec. 5).

Towards an automated approach to monitoring control loop performance

According to Starr et al. (2016), sixty percent of control loops in industrial processes can lose their effectiveness due to aging equipment, changes in raw materials, changes in operations, etc. As a result, the operation of industrial facilities can become unsteady; and the management of energy and raw material consumption can be negatively affected. Universities and industrial companies have started since the 1960s to look for CPA tools to diagnose the problems (controller tuning, sensor failure, etc.) that cause control system performance degradation. The large number and diversity of controllers in industrial processes make their monitoring and maintenance difficult. Therefore, control loops need to be observed by easy-to-use CPA tools to ensure their performance (Bauer et al. (2016)). Recently, data availability through IIOT along with the power of machine learning techniques (MLTs) have shown promise in improving CPA tools without being based on deep knowledge of industrial processes. The next subsection is devoted to demonstrating a brief summary of MLTs that have been developed in the literature to evaluate control loop performance.

Overview of Control Process Assessment Based on Artificial Intelligence

Using MLTs for CPA requires that data sets that reflect the performance of the control loop be accessed and stored. The data that can be stored are: setpoints (SPs), controlled variables (CVs), manipulated variables (MVs), and controller outputs (COs), binary signals that represent the status of the controller (AUTO/MANU). Also, disturbance can be modeled and added to the data for further analysis. It is worth to mention that the data collection for the CPA must be realized with the plant personnel (operators or control engineers). Once the data is collected, machine-learning (ML) based methods can be applied to evaluate the performance of control loops. Recalde et al. (2013) has integrated principal component analysis (PCA) as unsupervised ML techniques to assess the performance of PID controllers in steel rolling processes. Also, Chen and Wang (2010) combined PCA with ARMA to evaluate the performance of MIMO system. AlGhazzawi and Lennox (2009) developed a method based on PCA and partial least squares to monitor the performance of a model predictive control (MPC). Some works have implemented non-linear dynamical fractal analysis and slow feature analysis (SFA) as unsupervised MLTs to extract any variation or degradation in the control loops (Shang et al. (2019)). Zhao and Huang (2018) combined cointegration analysis and SFA to monitor the performance of control loops in a non-stationary process and time-variant operations conditions. Beyond that, the frequency domain and independent component analysis have been combined to detect and isolate abnormal oscillations (AOs) in a chemical plant. AOs affect the operation by adding variability, and then the control engineers face challenges to keep the process in the desired range (Xia et al. (2005)).

Also, non-linear PCA and adaptive neuro-fuzzy inference system (ANFIS) as supervised MLTs have been proposed to diagnose control valve stiction (Jeremiah et al. (2018)). The advantage of this kind of tool is that it can approximate a non-linear correlation between the variables of the control loops (MV, CV, etc.). In their recent work, Xu et al. (2019) proposed a methodology to go further than just detecting quality control deterioration to diagnose the root cause of the control performance degradation. They used a dissimilarity index which is the Mahalanobis distance to assess the performance of the controller, and support-vector machine as a pattern classifier to diagnose the root cause of poor control performance. It is worth mentioning that the authors defined a priory four patterns to represent what can cause a degradation of a control system. The patterns are noise mismatch, model mismatch, constraint saturation of the MVs, and constraint saturation of CVs.

Potential of Artificial Intelligence for Enhancing Control Performance Assessment Tools

Automation companies have developed several CPA tools to help control engineers to identify the poorest control loops. Current CPA tools guide control engineers in their diagnosis by classifying control loops as excellent, good, average, or poor (Mitchell et al. (2004)). Modern control systems integrate a high number of control loops wherein they are linked to several physical assets (sensors, valves, heavy machinery, etc.). Indeed, with the existing CPA tools, control engineers need to involve their knowledge with various graphs, performance indicators, reports, and correlations between control loops to track down the sources that lead to poor quality control loops. Due to this, and according to Bauer et al. (2016), control engineers are seeking more CPA tools with automated diagnostics and recommendations for appropriate actions to take. At the same time, despite the variety of ML methods for diagnosing the problem of poor control loops, these methods have not yet proven to be very effective in the industry due to their lack of robustness and high number of false alarms (Bauer et al. (2019)). In this context, many control loops go into manual mode due to performance degradation and engineers' lack of knowledge about the source of the problem. The manual use of control loops can be counter-productive to the investment in their deployment, which has already been implemented because of its beneficial impact on improving the operation of the industrial process. Therefore, the development of user-friendly CPA tools to automatically diagnose problems in control loops will be a key element to maximize the return on this investment. Furthermore, many of these CPA tools do not integrate the way a bad control loop can affect energy management, but instead, they are focused on the economic aspects. With the introduction of new environmental regulation that penalize the over-consumption of energy based on fossil fuels; future versions of CPA tools must consider the energy aspect.

As a first step, it is necessary to improve the CPA tools by including indicators directly related to energy performance. Thus, control loops are identified as deficient when the plant is affected economically and energetically (see Figure 1). Beyond that, we need to empower existing CPA tools with the ability to diagnose the origins of faulty control loops in an automated and efficient manner. Traditional CPA tools can generate a lot of information like plots (images), diverse indices to evaluate the performance of the control loop, reports, etc. We believe that AITs, as a decision support factor for humans, have the potential to analyze all this information to enhance current CPA tools by automating the diagnosis of control loop degradation. For this purpose, we have outlined an approach (see Figure 1) that will be detailed in the following paragraphs.

Existing CPA tools generate several indices, reports, images, etc. (see block (1)-Figure 1). AI technologies have the ability to merge all this information to upgrade CPA tools to the point where they automatically diagnose control loop malfunction. Interesting work in (Khamseh et al. (2016)) can be built on to develop AI tools such as the meta-classifiers and automated machine learning (AutoML) to obtain a fused decision (He et al. (2021). Recently, deep learning (DL) techniques, which are a subset of AI, have been successfully applied to image identification and speech recognition thanks to high-performance computing (HPC). Therefore, the different signals of the control loops need to be transformed into images (see block (2)-Figure 1), and then unsupervised DL methods (Agarwal et al. (2021)) can be used to extract the hidden knowledge to understand the origin of the deterioration of control loops. In addition, the obtained knowledge can be evaluated to label the images, with the content of each image representing one or more causes (valve jamming, equipment tuning issues, etc.). Once the images are labeled, supervised DL methods such as convolutional neural network (Wang and Oates (2015)) can be deployed in real-time to automatically find the source of the degraded control loops. Besides, it may happen that the supervised DL&ML cannot automatically diagnose the origin of the problem in the control system, so data-driven causality analysis (DDCA) (Landman and Jämsä-Jounela (2016)) can be used in this case to automatically generate a causality graph and determine the origin of the control malfunction. Some researchers in the literature have started applying DDCA to address the problem of propagation of oscillations between control loops (Landman et al. (2014)). Recently, several explainable AI (XAI) methods have been proposed to help experts better interpret the predictions of DL or ML methods (Ribeiro et al. (2016)), and this will open the door for future research to explore the combination of XAI and DDCA to improve the robustness and simplicity of the causality graphs.

Finally, in Figure 1, blocks (3) and (4) represent the part that we strongly suggest extending the power of the existing CPA tools. Block (3), which contains the AITs, receives and treats the information from both the block (2) and the equipment monitoring performance software to provide preliminary decisions to block (4). Control engineers must rely on these automated decisions from AITs and their knowledge of process control to take appropriate action to return the control system to proper performance.

Artificial intelligence for tuning of controllers

The focus of this section is to explore the potential of data and AI to tune the controllers (PID or MPC). Improper tuning is the most frequent issue related to controllers (Bauer et al. (2016)). The question is how data and AI can help extract more value and profit from existing controllers, in addition to the fact that the investment in these controllers has been improved and they have proven to meet the constraints of the process and ensure the safety of the operation. However, retuning controllers requires a lot of effort and is not a trivial task for an expert. Subsequently, the plant operators switch the controllers to manual mode when the target of the control loop is not attained. Subsequently, there is a need to provide engineers with an easy-to-use tool for controller tuning. Control engineers usually transform the control tuning (PID or MPC) to an objective function, then appropriate optimization algorithms can be applied to optimize that function, and finally, it is possible to find the best control policy (Amaral et al. (2018)).

Industrial processes are complex with many variables that need to be manipulated. In addition, their behavior is nonlinear and dynamic. Therefore, they require a very sophisticated control system with multiple competing objectives and many control parameters to tune. Consequently, applying optimization algorithms to tune controllers is challenging to implement in real time due to the curse of dimensionality, high computational requirements, slower convergence, suboptimal solutions, and handling uncertainty. Addressing these optimization problems in a tuning framework at a relatively low cost can be achieved with the availability of data through the IIOT and the power of AI as a decision tool. This has been the subject of several recently published papers. Thombre et al. (2020) proposed to use PCA to increase the computational efficiency in constructing the scheme of a multi-stage MPC. The proposed method was applied to control thermal energy storage in industrial clusters. Lucia and Karg (2018) chose DL techniques to find the optimal control policy of a nonlinear MPC in real time. Ira et al. (2018) integrated neural networks (NNs) to decrease the tuning time of MIMO MPC for controlling the air path of diesel engine. Vaupel et al. (2020) combined an NMPC with two NNs to not only improve the convergence of the optimization during the tuning but also to respect the constraints of the process.

While the above works have used unsupervised and supervised ML techniques to tackle the problem of tuning, the researchers in (Kofinas and Dounis (2019), Bøhn et al. (2021)) proposed to add the reinforcement-learning (RL) techniques on top to tune the parameters of the PID and MPC. In this case, the RL is used as an optimizer to find the parameters of existing PIDs and MPCs and there is no need to invest in new control strategies and simply use what is already installed. Furthermore, while the above studies have used AI in series with optimization algorithms, some recent work has begun to integrate AI into it to accelerate the search process

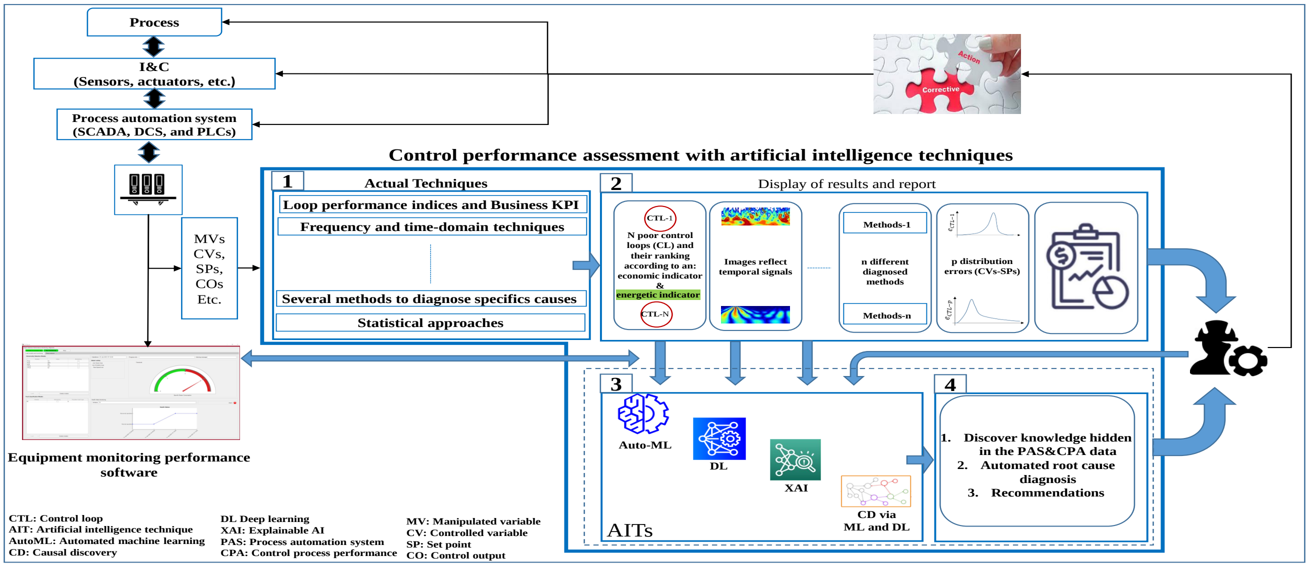

Figure 1: Control performance assessment tool powered by AI technologies

and convergence to optimal solutions (Song et al. (2019)). Combining AI with existing control techniques seems to be beneficial in maximizing the performance of control systems. Testing the performance and robustness of this combination before implementation is also crucial. The best virtual environment for commissioning is the digital process twin (DPT). Recently, IIOT has made it feasible to build highly accurate digital process twin that replicates the real process (Rosen et al. (2015)). This can also open the door to adaptive tuning as the reliability of tuning is increased by using DPT. One important point to add is that computing power (CPU and GPU) has advanced considerably compared to 30 years ago, which is a key factor to successfully integrating operations research and AI to regulate controllers in a seamless manner and with guaranteed robustness.

The objective of control strategies is to reach the set point in less time and with low variability, and most of the time they do not include information on energy consumption, and their purpose is only to make a business profit. We believe that with the power of computing and the ability of AI to handle complex conditions, it is possible to augment the existing and conventional control strategies (PID or MPC) to address multiple and sometimes conflicting goals, such as the need for high-quality and energy savings. Improving and enabling auto-tuning of controllers is now achievable, as never before, through a wide variety of AI technologies, operations research (OR) algorithms, and HPC. These varieties are available by using open-source Python libraries. AI technologies are offered by Scikit-learn, Keras, Tensorflow, etc. OR algorithms are accessible via Pyomo, Scipy optimize, Py-BOBYQA (Derivative-Free Optimizer), etc. Moreover, there is no need to add hardware, as all the above-mentioned open-source libraries for modeling complex processes and tuning controller parameters can be connected to different types of industrial DCS or PLCs (Figure 2). Most existing control systems are equipped with an open platform communication server (OPC). Therefore, OpenOPC (Python package) is one of the ways to connect AI and OR codes to the OPC server and subsequently to the DCS or PLC.

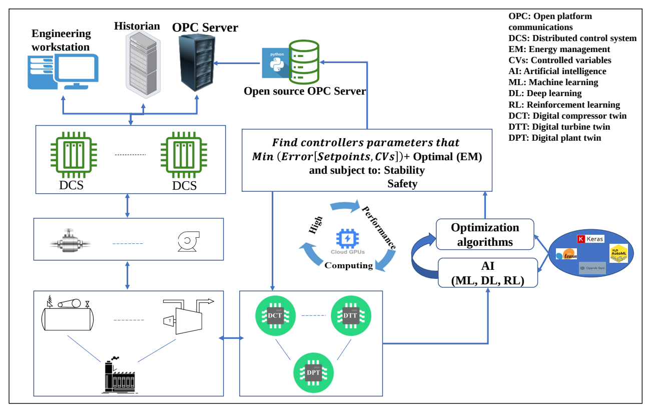

Figure 2: Improving energy management by enhancing control tuning

Future Vision

Why not revolutionize the way industrial processes are controlled where automation with conventional control methods is not possible? To do so, existing control strategies could be replaced by using only AITs for autonomous control. The appropriate AIT is RL (Syafiie et al. (2008)). It can be used as a model-free controller, where it is able to learn how to manipulate variables by interacting with DPT or real process. RL techniques can adapt themselves to control complex, non-linear, and changing dynamic process. However, the deployment of RL faces several barriers such as the safety and time of the agent to learn via trial-and-error procedure the policies of control. If this kind of sequential operations can be tolerated in some applications such as games, online advertising, etc., it is unacceptable to apply RL to control industrial processes where safety is a concern (Spielberg et al. (2019)). Consequently, the learning of RL must be on DPT, and the deployment of RL is related to the high fidelity of this DPT to reflect the real process.

As a result, and although some progress has been made (Cassol et al. (2018)), there is still much work to be done in this area to make RL the next-generation control technology that considers quality, energy efficiency, and unexpected events (Shin et al. (2019)). Future research and development must include more than just improving the algorithms used in RL. Therefore, there is a need to start at the stage of designing new processes or equipment to incorporate the feasibility of applied RL as a controller. This kind of work necessitates collaboration between experts in process engineering, automation, data acquisition, and AITs. Before concluding this research, which the focus is on how AITs can improve the exploitation of process controls to optimize the management of energy in industrial processes. A graphical description of the steps and scenarios to apply AITs is presented in Figure 3. In this figure, we have envisaged that energy efficiency can be held by several pillars where domain knowledge is the foundation. In this study, only the three pillars that are related to the control system are illustrated. The first pillar is "automation of the diagnosis of poor control systems". This pillar can be built with low investment, as the AITs to automate the diagnosis of poor control loops are available to be developed and deployed. The second pillar is "automation of tuning". This pillar requires more effort and cost to effectively bring together these different elements: DPT, OR, AITs, and HPC. On the other hand, the third pillar (AI as next-generation control technology) is seen as a way to self-driving process and at the same time enable optimal process optimization.

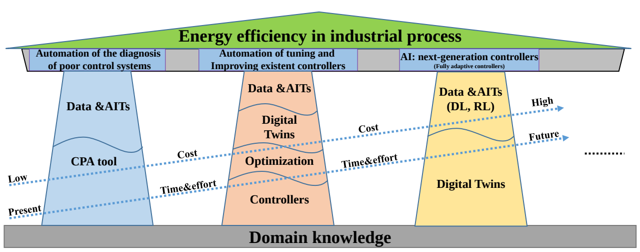

Figure 3: Toward improved control systems for energy efficiency in the industrial process

Conclusion

In this work, we reviewed the potential of artificial intelligence techniques (AITs) to improve existing control systems toward energy efficiency in industrial processes. We found that most control loops are not operational or fully exploited. Also, this study observed that the majority of methods that proposed in the literature are dedicated to monitor a single control loop, and the actual control performance assessment (CPA) tools are not able to diagnose the deficiency of control systems automatically. Then and in order to reduce the effort of control engineers to maintain the control systems, we suggested an approach to upgrade CPA tools through AITs to increase the automation of diagnosis. Besides, this study concluded that there is an opportunity to overcome the challenge of tuning the controllers by combining AITs, operations research, and high-performance computing. In addition, this work discussed that AITs have the potential to be the next-generation control technology by overcoming the safety and computational time issues associated with the application of reinforcement learning. Our future work intends to investigate and develop the methodology based on AITs and OR to auto-tune several PID controllers.

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