Online and Modular Energy Consumption Optimization of Industrial Robots

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***Abstract*—Industrial robots contribute to a considerable amount of energy consumption in manufacturing. However, modeling the energy consumption of industrial robots is a complex problem as it requires considering components such as the robot controller, fans for cooling, the motor, the friction of the joints, and confidential parameters, and it is difficult to consider them all in modeling. Many authors investigated the effect of operating parameters on the energy consumption of industrial robots. However, there is no prescriptive methodology to determine those parameter values because of the challenges in the modeling of industrial robots. This article investigates an industrial robot and the manufacturing process together and proposes a black-box model-based energy consumption optimization approach. Our contribution to the research is the new online and data-efficient methodology, prescriptive algorithm, and the analysis of operating parameters' effects on industrial robots' energy consumption. The proposed methodology is tested using two real FANUC industrial robots in three industrial settings.**

***Index Terms*—Energy consumption optimization (ECO), industrial robots (IRs), machine learning, manufacturing, optimization, robotic manufacturing.**

I. Introduction

INDUSTRIAL robots (IRs) consume a considerable amount of energy in the manufacturing industry. They account for 8% of the total energy consumption in production processes [1], and the energy consumption of IRs contributes 60% of the total follow-up costs after acquisition [2]. Sustainable manufacturing is one of the key directions of manufacturing, and the energy efficiency of IRs should be considered to achieve this. Reducing the energy consumption of IRs will automatically reduce operating costs and CO_2 emissions. The wide and increasing adoption of IRs makes it critical to optimize their energy consumption to ensure environmentally friendly characteristics [3].

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In this article, we analyze the effect of operating parameters, such as velocity, acceleration, spindle speed, and feed rate, on the energy consumption of IRs and develop a prescriptive methodology for finding better parameters. By prescriptive methodology, we mean a methodology that suggests operating parameters to minimize energy consumption.

II. Related Work

The energy consumption optimization (ECO) of IRs can be divided into two approaches: hardware-based optimization methods and software-based optimization methods [4].

The hardware-based approaches are mainly concerned with the energy-efficient design of IRs, such as using lightweight design [5], [6], adding energy recovery units [7], [8], or selecting energy-efficient robots for a given task [9], [10].

The software-based ECO methods of IRs are concerned with reducing the energy consumption without making hardware modifications, generally involving parameter modification [2], trajectory optimization [11], and operation scheduling [12]. Compared with the hardware approach, the software approach has the advantages of low cost and practical applicability [4].

In this article, we focus on the software-based ECO of IRs and specifically on optimizing the operating parameters of IRs to reduce energy consumption during a manufacturing operation and analyze recent works in this direction.

Paryanto et al. [1] developed a modular approach to modeling of an IR to analyze the power consumption and its dynamic behavior. The main conclusion is that the energy consumption of an IR can be reduced by reducing the weight of tooling systems, smoothing the motion, and finding optimal speed, which should not be too fast and too slow. The proposed approach relies on a mathematical model, which may limit its applicability to other types of robots.

Liu et al. [13] discussed the effect of inertial and friction parameters on the energy consumption of an IR. They analyzed the relation between the robot's speed and energy consumption and came to a similar conclusion as in [1]. The developed solution is robot specific and difficult to generalize to other types of robots.

Gadaleta et al. [14] proposed the ECO method using an IR model and simulation software to show that adjusting acceleration and velocity parameters can reduce up to 19.8% of energy consumption. However, the proposed method is model based, assuming that an IR can be accurately modeled.

Zhang and Yan [15] used neural networks and genetic algorithms for modeling and optimizing the energy consumption of IRs. The dataset is very small: 729 samples (81 × 9), and it is difficult for neural networks to generalize from such a small dataset.

Gadaleta et al. [2] investigated the effect of acceleration, velocity, motion type, viscous friction, and delay time in closing the IR's mechanical brakes on the energy consumption of IRs to show that it is possible to reduce energy consumption by 50% with appropriate parameters. Even though the authors shared the methodology and the collected data, findings in this research cannot be generalized to other robots due to different parameters and working conditions.

Yan and Zhang [16] proposed a transfer-learning method for the ECO of IRs. However, they noted the limitations of their approach, such as the limited motion range for prediction and the need for sufficient experiments to ensure the accuracy of energy consumption.

Riazi et al. [17] proposed a framework for IR energy and peak power optimization. This article has investigated multirobot scenarios, which is relevant in a real manufacturing scenario.

III. Challenges and Contributions

The analyzed literature above clearly indicates that operating parameters, such as acceleration, velocity, payload, and motion type, affect the energy consumption of an IR. The majority of authors used simulation software tools to model and predict the energy consumption of IRs. They all agree on the nonlinear relationship between the operating parameters and energy consumption. However, finding the optimal operating parameters for energy consumption reduction is still a difficult challenge that needs to be addressed. The challenges of the existing solutions are as follows.

1) *Modeling of an IR:* An accurate model of an IR is difficult to achieve due to heterogeneous components contributing to IR energy consumption and other parameters of IRs, such as the trajectory formula, which is unknown and often protected as a trade secret by the robot manufacturers. In general, modeling the energy consumption of an IR is difficult, imprecise, and not generalizable to other robots. Modeling and simulation-based approaches usually address only a specific type of robot, and for every different type of robot, a separate model should be developed.
2) *Data efficiency:* Data-driven methods solve the challenge of explicit modeling, but they face data efficiency problems. Generally, data-driven approaches require a huge amount of data to make reasonable predictions. Transfer-learning-based methods, such as in [16], can be utilized to overcome the data limitations, but as the authors of this article have already mentioned, the prediction accuracy is determined by the datasets gathered in experiments. A new prediction task requires previous datasets to be reprocessed and new prediction models rebuilt from scratch.

Hence, this article has the following three main contributions:

1) a prescriptive methodology for the modeling and optimization of the energy consumption of IRs;
2) an online and modular meta-algorithm for the ECO;
3) data analysis of the effect of operational parameters on the energy consumption of IRs.

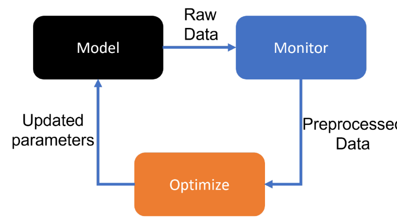

Fig. 1. Online and modular optimization loop.

IV. Methodology

Manufacturing requirements constantly change, and there is a need to adapt quickly to new scenarios, making it flexible for a wide range of manufacturing applications. Hence, the ECO methodology should be modular and online to adapt to changing requirements.

The modularity of methodology is important to abstract the complexities of the optimization algorithms. The abstraction allows plugging application-specific optimization algorithms in or out as appropriate. This way, whenever a better or more suitable algorithm is developed, it can be directly plugged into a meta-algorithm.

The ability to optimize process parameters online on a real IR without stopping production is required because of business costs. This way, an operator has an option to control adjusting process parameters at a certain percentage of production cycles to avoid production disruptions.

In this section, considering the above requirements, we present an online and modular methodology for optimizing the energy consumption of IRs. The methodology consists of three main steps, as shown in Fig. 1, and each step is discussed in the following subsections.

A. Modeling

Instead of explicitly modeling an IR or using simulation-based methods, we propose to use a black-box model. The black-box model allows treating the whole system without knowing its internal workings and gives flexibility to transferring it to different robots and manufacturing processes. Consequently, we propose to model an IR and a manufacturing process together using a black-box function, whose internal workings are not known or hidden but return different energy consumption as output depending on input parameter values

$$f : \mathbb{R}^d \to \mathbb{R}. \tag{1}$$

The above black-box function f receives a d-dimensional vector of parameter values $\mathbf{x} \in \mathbb{R}^d$. The input vector $\mathbf{x}$ to the black-box function f is constrained using lower and upper bound parameter values' vectors $\mathbf{l} \in \mathbb{R}^d$ and $\mathbf{u} \in \mathbb{R}^d$, respectively. In a real robotic manufacturing scenario, $\mathbf{x}$ will be the set of adjustable operating parameters, such as velocity, acceleration, and motion type. The lower and upper values, $\mathbf{l}$ and $\mathbf{u}$, will be minimum and maximum allowed parameter values depending on the manufacturing process constraints.

Robotic manufacturing systems are complex, and different factors can affect the energy consumption of an IR. In addition, the energy consumption measurements can be noisy depending on the energy monitoring solutions. Thus, the developed methodology should be robust to such noisy outputs. To deal with the measurement noises directly inside the optimization loop, we extend the output of the black-box model with a noise value, and the observed energy consumption of a black-box model $f(\mathbf{x})$ is measured as follows:

$$E(\mathbf{x}) = f(\mathbf{x}) + \epsilon \tag{2}$$

where the noise parameter ϵ is normally distributed

$$\epsilon \sim \mathcal{N}(0, \sigma^2). \tag{3}$$

Considering the above model, the ECO of an IR performing a manufacturing process is formulated as follows:

$$\min_{\mathbf{x}\in P} E(\mathbf{x}) \tag{4}$$

where

$$\mathbf{P} = \{\mathbf{x} \in \mathbb{R}^d \mid l_i \leq x_i \leq u_i \; \forall i = 1, \ldots, d\} \tag{5}$$

is the feasible set of solutions.

Most real-world robot tasks require stops or a constant speed at specific program points. The optimization problem can be further broken down into smaller optimizations, which makes the method scalable w.r.t. the length of the robot program.

The black-box optimization reasoning can be applied to multiprocess robotic manufacturing by considering each process separately and independently optimizing energy consumption. The optimization problem becomes

$$\min_{\mathbf{x}_1\in \mathbf{P}_1} E(\mathbf{x}_1) + \cdots + \min_{\mathbf{x}_N\in \mathbf{P}_N} E(\mathbf{x}_N) \tag{6}$$

where N is the number of separable and independent processes.

B. Monitoring

The important step in ECO is monitoring the energy consumption of an IR.

The different sources for monitoring are smart meters, current and voltage clamps, or machine-integrated devices that provide out-of-the-box instantaneous power consumption. Some IRs can provide the power consumption for each joint of the robot directly from a robot controller.

The sampling rate of energy data collection is important and depends on the application. For example, analyzing the motion profiles of IRs requires a relatively high sampling rate of energy consumption. While a high sampling rate gives much data that will be difficult to preprocess in real time, a low sampling rate might miss important information, such as the start and end of the operation cycles. Therefore, a sampling rate should be chosen carefully depending on the application and computing power capabilities. Usually, a high acquisition frequency is required to obtain good measurements, such as in [2] and [14]. However, the acquisition frequency is limited by the monitoring hardware limitations.

Once the data are acquired, they need to be resampled to match time stamps and stored in local storage. The energy data are usually recorded in regular time stamps, which result in time-series data. There are special database solutions for storing time-series data, such as InfluxDB. In addition, relational database methods are used in energy data for their reliability. However, some monitoring solutions store the collected energy in device memory using comma-separated value files. The choice of storage solutions greatly affects the application. High-frequency big data files require special solutions, such as Hadoop and Spark, that can deal with the high volume property of big data [18].

C. Optimization

With the ECO problem mathematically formulated in Section IV-A and with a monitoring approach detailed in Section IV-B, we can then apply the data to solve the problem using suitable optimization algorithms. However, the nature of the black-box models prevents using first- or second-order methods, such as gradient descent, Newton's method, or quasi-Newton methods. In such cases, derivative-free optimization methods are commonly used. Many algorithms exist to solve black-box optimization problems. Still, the optimization of energy consumption of robotic manufacturing systems should be data efficient because every experimental trial is time consuming and limits the amount of data that can be collected in a reasonable time.

Another problem in optimization is "the no free lunch" (NFL) theorem [19]. According to the NFL theorem, "any two algorithms are equivalent when their performance is averaged across all possible problems," i.e., there is no single best algorithm that performs on all the problems.

We propose a modular meta-algorithm that can accept suitable application-dependent optimization algorithms to address the challenges above. This meta-algorithm is called the online and modular energy consumption optimization (OMECO) meta-algorithm, shown in Algorithm 1.

The OMECO algorithm starts with an initial guess of input parameters. The initial guess can be chosen randomly or using the previously gathered knowledge. For example, initial velocity and acceleration values can be started from 50% values or selected based on input parameters of similar manufacturing processes.

The OMECO meta-algorithm is designed to be able to run online without stopping production. This feature is achieved by running the optimization loop in the background because some algorithms take a long time to finish the optimization step. Whenever the new suggested parameters become available, they are changed in the IR. If the new parameters yield less energy consumption, they are kept; otherwise, the previous best parameters are reverted.

Another feature of the OMECO algorithm is exploration-and-exploitation, which helps run the optimization only at some production cycles. This feature of the algorithm is controlled

Algorithm 1: OMECO Algorithm.

Require: An initial guess $\mathbf{x}_0$, the lower bound $\mathbf{l}$, the upper bound $\mathbf{u}$, the total number of iterations n, the exploration parameter α, an optimization algorithm Φ, a data-structure for storing dataset $\mathcal{D}$

$y_0 \leftarrow E(\mathbf{x}_0)$ ▷ Measure energy consumption
$y_{\text{best}} \leftarrow y_0$ ▷ Best energy consumption
$\mathbf{x}_{\text{best}} \leftarrow \mathbf{x}_0$
$\mathcal{D} \leftarrow \{(\mathbf{x}_0, y_0)\}$ ▷ Set the initial dataset
$i \leftarrow 1$
while $i < n$ **do**
  Sample p from uniform distribution $U(0, 1)$
  if $p \leq \alpha$ **then**
    $i \leftarrow i + 1$
    $\mathbf{x}_i \leftarrow \Phi(i, \mathbf{l}, \mathbf{u}, \mathcal{D})$ ▷ Call the optimization step
    $y_i \leftarrow E(\mathbf{x}_i)$
    $\mathcal{D} \leftarrow \mathcal{D} \cup \{(\mathbf{x}_i, y_i)\}$ ▷ Extend the dataset
    if $y_i < y_{\text{best}}$ **then**
      $\mathbf{x}_{\text{best}} \leftarrow \mathbf{x}_i$
      $y_{\text{best}} \leftarrow y_i$
    end if
  end if
end while
return $\mathbf{x}_{\text{best}}, y_{\text{best}}, \mathcal{D}$

using the α parameter. Setting $\alpha = 1$ always tries to find an optimal solution, while setting $\alpha < 1$ will run optimization stochastically. For example, $\alpha = 0.1$ will run an optimization algorithm on average every tenth iteration.

OMECO wraps around other optimization algorithms, Φ; therefore, they can be plugged into the meta-algorithm whenever the better choices become available.

The OMECO algorithm accepts the following input parameters:

1) $\mathbf{x}_0$: an initial parameter guesses either choosing randomly or using the human operator's knowledge;
2) $\mathbf{l}$: the lower bound of $\mathbf{x}_0$;
3) $\mathbf{u}$: the upper bound of $\mathbf{x}_0$;
4) n: the total number of optimization steps;
5) α: the exploration parameter. This parameter controls how often the optimization should be performed;
6) Φ: an application-dependent optimization algorithm.

The output of the OMECO algorithm is the parameters that yield the least energy consumption and the collected data for use with similar processes.

In the next section, we experimentally validate the proposed modeling methodology and OMECO algorithm on a representative manufacturing process using a real IR.

V. Use Case

This section consists of three experimental validations of the proposed approach.

The first experiment analyzes the application of the proposed methodology and algorithm on a real IR using a representative pick-and-place manufacturing process. The objectives of the first experiment are to find the optimum parameters and use them to gather insights into how different motions might have different optimum parameters.

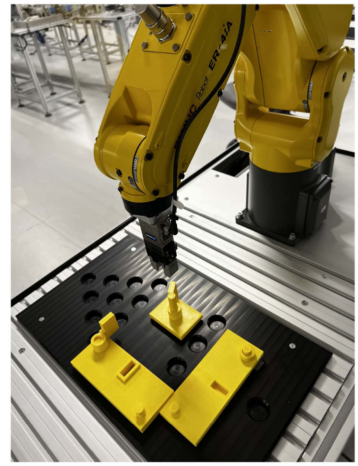

Fig. 2. Experiment setup representing a common pick-and-place operation in a robotic manufacturing.

The second experiment involves a more complex industrial bin-picking application where the movements are not preprogrammed and require online task adaptation. The objective of the second experiment is to provide an illustrative example for wider application scenarios.

In the third aerospace manufacturing experiment, a robotic drilling system was utilized to optimize energy consumption while drilling holes in aluminum and acrylic materials. The experiment aims to identify the ideal spindle speed and feed rate parameters that reduce energy consumption.

A. Experiment 1: Pick-and-Place Operation

1) Experimental Setup: The experimental setup for the first experiment is shown in Fig. 2 and includes a FANUC ER-4*i*A IR and a pick-and-place process. The FANUC robot controllers allow access to the energy data directly out of the box. It is possible to change the resolution of data collected directly inside the controller. This approach might differ for different types of robots, but the overall methodology will be the same.

A pick-and-place process is a very common process in robotic manufacturing, and the whole process shown in Fig. 2 can be divided into the following operations.

1) **M1.** Move to the "pick approach" pose.
2) **G1.** Open the gripper.
3) **M2.** Move to the "pick" pose.
4) **G3.** Close the gripper.
5) **M3.** Move to the "pick retract" pose.
6) **M4.** Move to the "place approach" pose.
7) **M5.** Move to the "place" pose.
8) **G3.** Open the gripper.
9) **M6.** Move to the "place retract" pose.
10) **M7.** Move to the "home" pose.

The labels M and G refer to different types of actions, and there are seven motions labeled as M and three gripping actions

TABLE I
MINIMUM AND MAXIMUM ALLOWED VELOCITY AND ACCELERATION VALUES FOR MOTIONS M1–M7

Motion type	Velocity range	Acceleration range	Configurations #
Motion 1	$[50, 100]$	$[50, 100]$	$50 \times 50 = 2500$
Motion 2	$[5, 40]$	$[5, 40]$	$35 \times 35 = 1225$
Motion 3	$[5, 40]$	$[5, 40]$	$35 \times 35 = 1225$
Motion 4	$[50, 100]$	$[50, 100]$	$50 \times 50 = 2500$
Motion 5	$[5, 40]$	$[5, 40]$	$35 \times 35 = 1225$
Motion 6	$[50, 100]$	$[50, 100]$	$50 \times 50 = 2500$
Motion 7	$[50, 100]$	$[50, 100]$	$50 \times 50 = 2500$

labeled as G. The parameters of the motions can be adjusted to affect the energy consumption. In this experiment, the operating parameters for each motion are velocity, acceleration, and motion type. FANUC robot controllers allow setting only two types of motions: J [Joint] and L [Linear]. Hence, we tune only the velocity and acceleration values of seven motions for the minimum energy consumption objective.

While tuning the operating parameters of each motion, careful attention should be given to holding constraints, such as maximum execution time and the safety of pick-and-place operation. The maximum acceptable execution time usually depends on the manufacturing operation requirements. In this experiment, the maximum allowed execution time was set to 20 s by a human operator for one pick-and-place operation. In a real manufacturing scenario, there are some challenging situations where the energy consumption is demanding, and the robot performing tasks requires a given velocity and acceleration. Therefore, each parameter was constrained separately besides a maximum execution time constraint to meet such requirements.

For our experiment, the minimum and maximum values were selected based on picking and placing relatively fragile 3-D-printed parts. The human operator ensured the safe values for velocity and acceleration, as shown in Table I. Table I also shows the number of possible configurations for each motion type. These values are fixed for this specific manufacturing process, and the parameter values are displayed in percentages of the robot's maximum possible velocity and acceleration.

To verify the modularity of the OMECO and its applicability to an industrial setting, we experimented with three different popular algorithms: random search (RS) [20], generalized simulated annealing (SA) [21], and Bayesian optimization (BO) [22]. The choice of the algorithms was task dependent. There are many different types of algorithms in the literature, but not all of them are suitable for solving black-box optimization problems. In this case, we do not have any derivative information, and the space of optimization algorithms is limited only to derivative-free optimization algorithms.

We applied the proposed methodology and OMECO algorithm to solve the above ECO problem as follows.

1) In the first step, the energy data were obtained through a FANUC robot controller. The instantaneous power data were collected every 50 ms because of the limitations of the robot controller and network latency. The energy data were resampled to match the time stamps and make regular time intervals. It was stored in the SQLite database for calculating the total power consumption, which is then fed to the model.
2) In the second step, the optimization loop continuously optimizes the parameters.
3) Finally, in the third step, new parameters are recommended for the robot.

The whole optimization procedure continues until the termination criteria are met. Usually, the termination criterion is when the cost function, i.e., energy consumption, stops changing. However, for a fair comparison of the optimization algorithms, the termination criterion, in this case, is the predefined total number of iterations.

In the next subsection, we present our experimental results and analysis of algorithms and the effect of motion parameters on the ECO of IRs.

2) Experimental Results: To benchmark with the proposed ECO methodology, as a baseline, we measured the energy consumption of the robot with minimum and maximum allowed parameter configuration for the above-described pick-and-place process. For simplicity, we call the minimum allowed parameter configuration $B_{\min}$ and the maximum allowed parameter configuration $B_{\max}$. Since the energy consumption measurement is noisy, we performed the same pick-and-place process ten times for each configuration.

RS, SA, and BO are nondeterministic algorithms, meaning that their output will differ in every run even with the same set of input parameters. Therefore, each algorithm was run for 100 iterations ten times for a fair comparison. The box plots and corresponding statistics are shown in Fig. 3 and Table II, respectively.

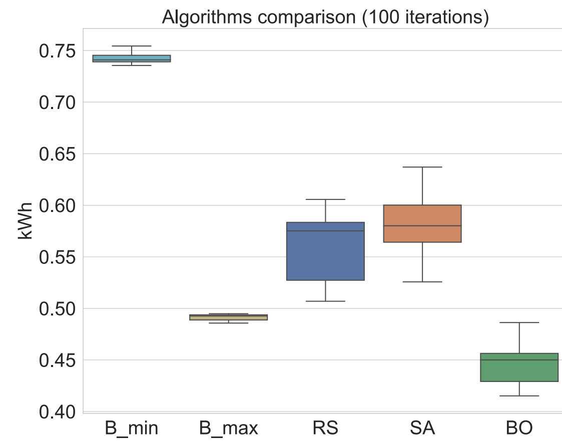

Fig. 3. Comparing algorithms.

TABLE II
EXPERIMENTAL STATISTICS

Method	Minimum	Maximum	Median	Mean	Standard deviation
$B_{\min}$	0.736	0.754	0.741	0.743	0.006
$B_{\max}$	0.486	0.495	0.493	0.491	0.003
SA	0.507	0.606	0.575	0.559	0.033
RS	0.526	0.637	0.580	0.579	0.033
BO	**0.415**	**0.486**	**0.450**	**0.446**	0.020

Values are in kilowatthour.

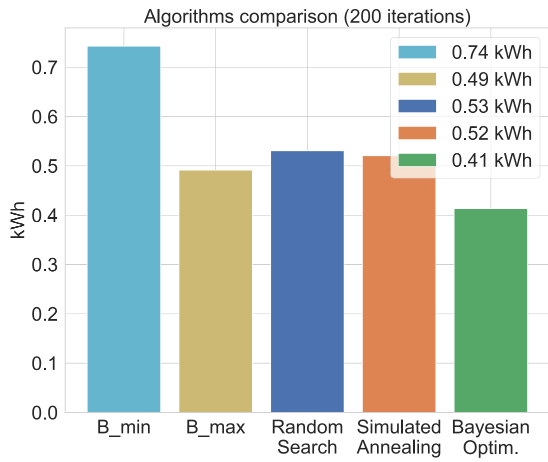

Fig. 4. ECO results for the pick-and-place process.

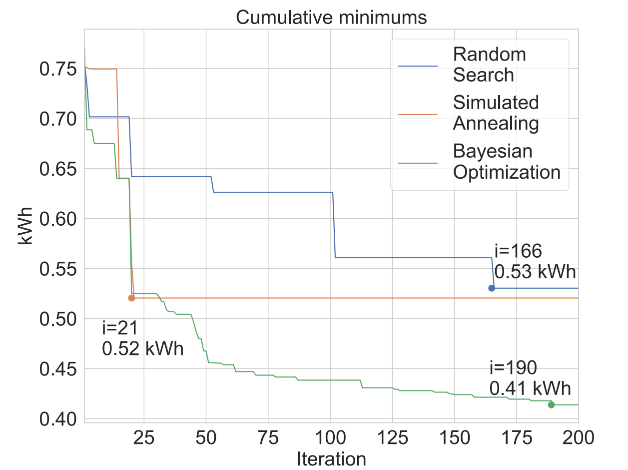

Fig. 5. Cumulative minimum values for three different optimization results.

TABLE III
OPTIMIZED VELOCITY AND ACCELERATION VALUES

Motion type	RS		SA		BO	
	v.	a.	v	a.	v.	a.
Motion 1	100	52	96	50	98	64
Motion 2	13	30	19	31	19	40
Motion 3	6	32	29	30	19	39
Motion 4	46	68	88	92	50	100
Motion 5	26	34	13	31	12	40
Motion 6	57	91	96	88	75	85
Motion 7	95	63	66	63	71	72

This table shows velocity (v.) and acceleration (a.) values found by three optimization algorithms: RS, SA, and BO.

From Fig. 3, we can observe that the maximum allowed parameter configuration yields less energy consumption than the minimum allowed parameter configuration. However, in general, the relationship is nonlinear, and the maximum allowed parameter configuration does not yield the optimal energy consumption, as shown by many authors [2], [14], [15], [16], and validated by our results below.

From Fig. 3 and Table II, we can see that all the optimization algorithms outperform the $B_{\min}$ baseline. However, only the BO outperforms $B_{\max}$. The BO outperforms $B_{\max}$ on average by 9%, and the worst case of BO is similar to the best case of $B_{\max}$, which proves that the fastest possible option is not the most energy optimal motion.

We ran the OMECO algorithm with three previously chosen optimization algorithms starting from the same initial parameter configuration for 200 iterations more to check the possibility of further improvement. Fig. 4 shows energy savings achieved by the optimization algorithms compared with baseline results.

We can observe from Fig. 4 that RS, SA, and BO outperform $B_{\min}$ by 28.38%, 29.73%, and 44.59%, respectively. However, RS and SA methods do not outperform $B_{\max}$, because, usually, RS and SA methods require thousands of iterations to find the optimal solution. The BO outperforms $B_{\max}$ by 16.32% in as few as 40 iterations.

The parameter values found by three optimization algorithms are shown in Table III. As shown in Table III, the discovered velocity and acceleration values are not the fastest or slowest motion yielding values. These results are consistent with the literature's related work and show the nonlinear relationship between operating parameters and energy consumption.

3) Data Efficiency Analysis: Here, we analyze the data efficiency of the proposed approach.

Fig. 5 displays the cumulative minimum curves for each optimization algorithm for 200 iterations. The cumulative minimum curves are useful for visualizing the speed of finding solutions. As shown in Fig. 5, the SA algorithm finds its solution in 21 iterations. However, the algorithm fails to improve at all after that. The RS algorithm finds its best solution in 166 iterations. However, the found solution is not better than the solution found by the SA algorithm. The BO finds its best solution in 190 iterations. However, after 30 iterations, it outperforms the SA algorithm, and after 40 iterations, it outperforms all the baselines. Consequently, it can be concluded that BO is a relatively data-efficient algorithm.

The most efficient methods for energy consumption of IRs in the literature are work by Zhang and Yan [15], which required 729 samples, and work by Yan and Zhang [16], which required 900 samples. Our optimization methodology starts improving the energy consumption after only 40 samples. The other strength of the proposed methodology is that data can be added sequentially without collecting in advance. Hence, this method can be used in an already running production system that can dynamically change operating parameters that affect energy consumption.

4) Analysis of Motion Parameters: Fig. 6 shows the energy consumption outcome as a function of velocity and acceleration parameters. The left figure shows the energy consumption when all the parameters are fixed except the velocity parameter of motion M7. One can observe that the relationship between velocity and energy consumption is nonlinear, i.e., the minimum energy consumption is achieved when the velocity is around 70%. Similarly, the right subfigure shows the energy consumption as a function of the acceleration parameter of motion M7. The nonlinearity property also holds for this parameter. Fig. 7 shows

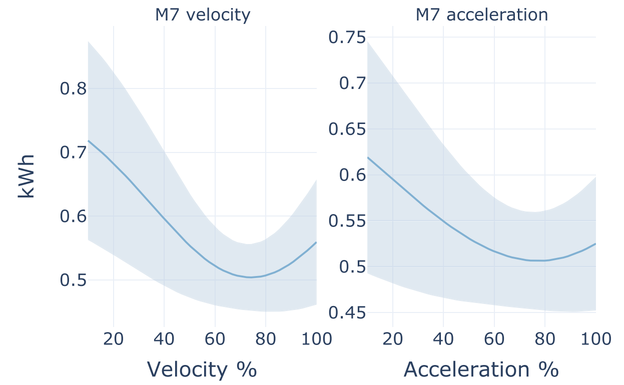

Fig. 6. Slice plot for motion 7. (Left) Velocity varies, other parameters are fixed. (Right) Acceleration varies, others are fixed.

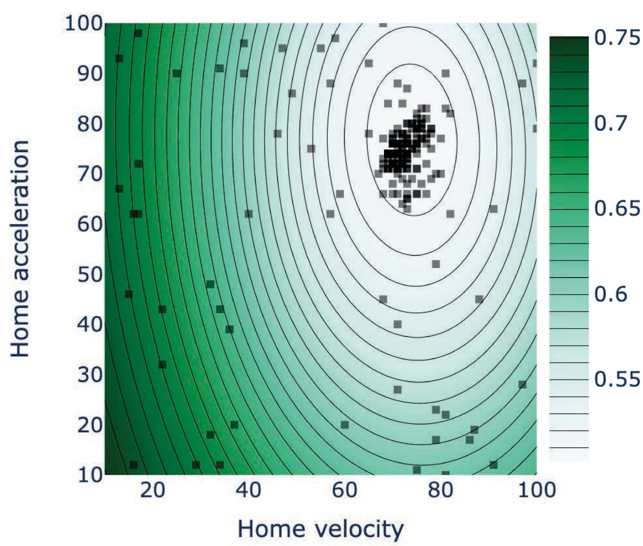

Fig. 7. Contour plot for motion M7 as a function of velocity and acceleration. Other parameters are fixed.

the contour plot of energy consumption as a function of velocity and acceleration parameters together. This plot also reveals how the BO reaches the optimal point. Initially, parameters are sampled from different regions. However, as the optimization progresses, more and more parameters are sampled in the neighborhood of the optimal parameters.

B. Experiment 2: Optimization of Bin Picking

In this experiment, we optimized the bin-picking process, which involves picking randomly positioned objects from a bin containing three different parts, as shown in Fig. 8. The objective of the process is to pick the parts and place them in their corresponding containers.

The picking of each object involves seven different motions, but the parameters for these motions differ for each object, with different lower and upper bounds. In addition, the robot must stop and select the next object to pick after each pick-and-place operation. This results in a total of 21 parameters to be optimized.

However, as the number of parameters increases, the efficiency of black-box optimization algorithms, such as BO, decreases. To address this issue, we performed two scenarios for optimizing energy consumption. In the first scenario, we optimized all the 21 parameters together. In the second scenario, we measured and optimized the parameters for each part separately, while the bin-picking process was running, allowing for more efficient optimization.

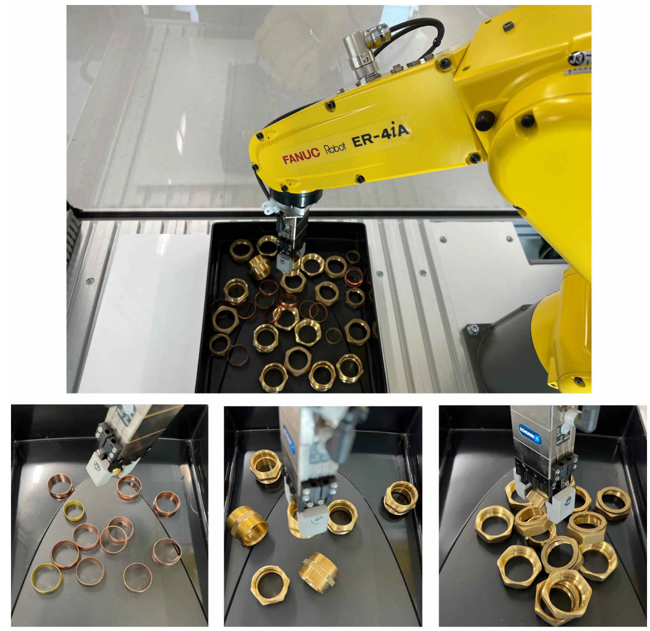

Fig. 8. Bin consists of three different parts with variable shapes and weights. The task is to sort the parts in their respective containers.

In the present experimental setup, the optimization for each of the scenarios was run for a total of 200 iterations, which is similar to the number of iterations used in previous experiments. The results of each optimization scenario were compared to $B_{\min}$ and $B_{\max}$ baselines, as shown in Fig. 9.

In the bin-picking experiment, the learning curves presented in Fig. 9 reveal that the combined optimization approach did not yield better results than those of the $B_{\max}$ baseline. The increased number of parameters, which totaled 21 in this scenario, likely contributed to this outcome. With more dimensions, the search space expands, requiring the optimization algorithm to perform a larger number of search iterations before discovering optimal values.

In contrast, the scenario where each part was optimized individually resulted in better parameter values than those achieved with the $B_{\max}$ baseline. Once satisfactory motion parameters are identified, the optimization process can be halted, and the discovered parameter values can be applied to subsequent iterations. In this particular experiment, the individual optimization approach led to an average energy savings of 25%.

Further emphasizing the effectiveness of the individual optimization approach, Table IV presents a comparison of energy savings for the individual scenario against $B_{\min}$, $B_{\max}$, and combined scenarios. With energy savings of 45.88%, 25%, and 27.37%, these results demonstrate the superior efficiency of optimizing the parameters for each part individually in the bin-picking experiment.

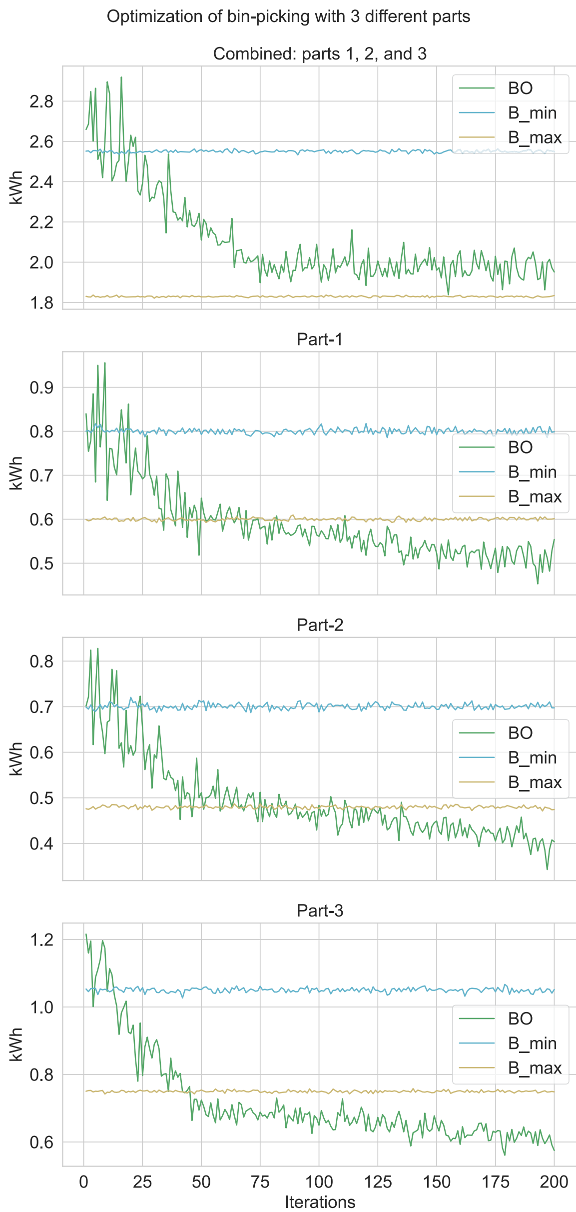

Fig. 9. Plot shows the optimization results of bin picking for three different parts separately and the combined optimization.

TABLE IV
ENERGY SAVINGS COMPARISON FOR BIN-PICKING EXPERIMENT

Comparison	Energy savings
Individual versus $B_{\min}$	45.88%
Individual versus $B_{\max}$	25.00%
Individual versus combined	26.20%

C. Experiment 3: Optimization of Drilling

In this aerospace manufacturing experiment, a FANUC M800iA robot controller and a drilling end effector controlled by a computer numerical control (CNC) machine were utilized to optimize the energy-efficient drilling of holes through 6-mm-thick aluminum and 6-mm-thick cast acrylic layers. The experimental setup is illustrated in Fig. 10. The robotic arm's approach and retract positions were fixed, and the total drilling

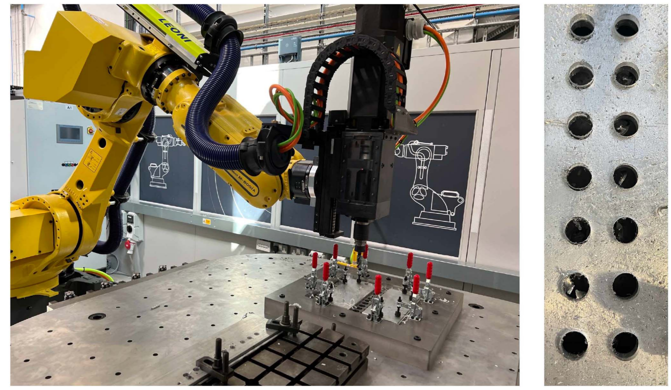

Fig. 10. Optimization of drilling. The aim is to energy efficiently drill holes through 6-mm-thick aluminum and 6-mm-thick cast acrylic layers.

TABLE V
PARAMETER RANGES FOR THE DRILLING EXPERIMENT

Parameter	Range
Spindle speed	1500–2500 r/min
Feed rate	150–180 mm/min

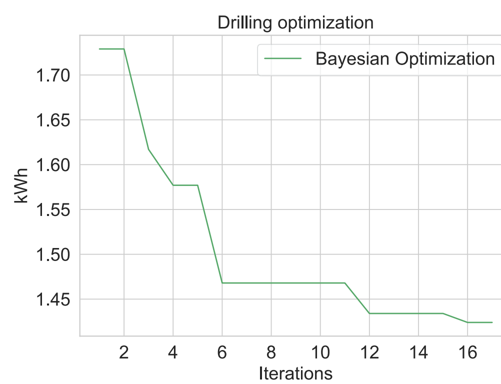

Fig. 11. Cumulative minimum values for drilling optimization results.

time was constrained to be within 20 s. The maximum allowed spindle speed was set to vary between 1500 and 2500 r/min, while the feed rate ranged from 150 to 180 mm/min, as shown in Table V.

The primary objective of this experiment was to determine the optimal spindle speed and feed rate parameters to minimize energy consumption during the drilling process. BO was employed in real time on the actual equipment to achieve this goal. The total energy consumption, which encompassed the spindle and servo motors, was measured and subsequently fed back into the OMECO algorithm. This algorithm suggested new parameter values, and the optimization loop continued until convergence was reached, which was determined when no further improvements were made, and the algorithm began suggesting the same parameters repeatedly.

After only 25 iterations of the optimization process, energy consumption savings of 17.64% were achieved. The cumulative minimum plot for the BO results is displayed in Fig. 11, while Fig. 12 presents the slice plots of energy consumption in relation to spindle speed and feed rate parameters. These results

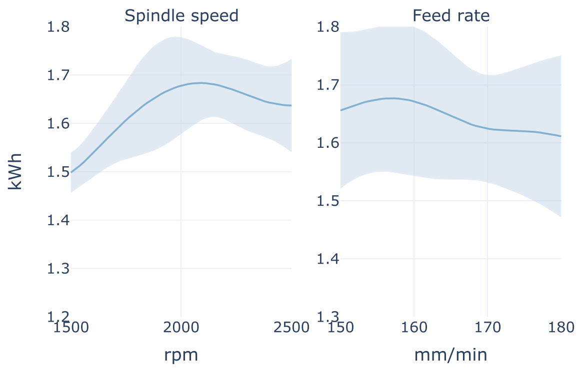

Fig. 12. Slice plot for drilling. (Left) Spindle speed varies and the feed rate is fixed. (Right) The feed rate varies and spindle speed is fixed.

are consistent with previous experiments, demonstrating the nonlinear relationship between process parameters and energy consumption and emphasizing the importance of optimization for energy-efficient manufacturing processes.

The drilling experiment showcased the effectiveness of BO in identifying optimal parameter values for energy efficiency. As evidenced by Fig. 11, substantial energy savings were obtained, reinforcing the value of optimization techniques in manufacturing processes.

VI. Conclusion

In this article, we examined software-based ECO for IRs and introduced a novel, modular, and prescriptive optimization methodology. This methodology treated the IR and manufacturing process as a black-box model and was resilient to measurement noise. Our analysis corroborated the nonlinear relationship between energy consumption and IR operation, as previously demonstrated by other researchers. However, our approach uniquely enabled the online optimization of operating parameters without requiring extensive data.

Our experiments illustrated the applicability of this proposed method for optimizing robotic manufacturing processes using black-box optimization algorithms. Furthermore, the results from the second scenario indicated that optimization can be divided into subproblems when feasible.

As energy consumption is a critical aspect of sustainable manufacturing, exploring the application of this methodology to other manufacturing equipment presents an intriguing research opportunity. Future research directions include examining various black-box optimization algorithms, their limitations, and their advantages across manufacturing equipment and processes.

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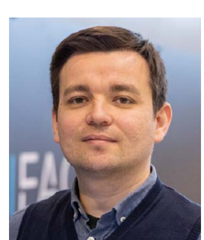

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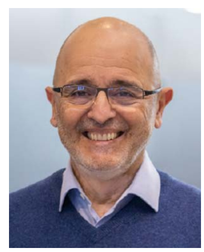

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