

Online and Modular Energy Consumption Optimization of Industrial Robots

Agajan Torayev, Giovanna Martínez-Arellano, Jack C Chaplin, David Sanderson, and Svetan Ratchev

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 work 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 was tested using two real FANUC industrial robots in three industrial settings.

Index Terms—robotic manufacturing, energy consumption optimization, industrial robots, machine learning, manufacturing, optimization

I. INTRODUCTION

Industrial robots (IR) 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 CO₂ emissions. The wide and increasing adoption of IRs makes it critical to optimize their energy consumption to ensure environmentally friendly characteristics [3].

In this work, 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.

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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, like 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 work, we focus on 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.

In [1], the authors developed a modular approach to modelling 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 be not too fast and not too slow. The proposed approach relies on a mathematical model, which may limit its applicability to other types of robots.

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

In [14], the authors 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.

In [15], the authors use neural networks and genetic algorithms for modeling and optimizing the energy consumption of IRs. The dataset is very small: 729 samples (81x9), and it is difficult for neural networks to generalize from such a small dataset.

In [2], the authors 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 can not be generalized to other robots due to different parameters and working conditions.

In [16], the authors proposed a transfer-learning method for ECO of IRs. However, the authors 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.

In [17], the authors proposed a framework for industrial robot energy and peak power optimization. The work has investigated multi-robot scenarios, which is relevant in 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. All authors 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 existing solutions are:

- *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.
- *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 the paper 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 work has three main contributions:

- 1) A prescriptive methodology for modeling and optimization of the energy consumption of industrial robots
- 2) An online and modular meta-algorithm for the energy consumption optimization
- 3) Data analysis of the effect of operational parameters on the energy consumption of industrial robots

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 energy consumption optimization 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 industrial robot 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.

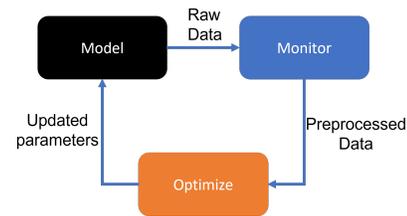


Fig. 1: Online and modular optimization loop

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 returns different energy consumption as output depending on input parameter values:

$$f : \mathbb{R}^d \rightarrow \mathbb{R} \quad (1)$$

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. Also, 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 below:

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

where the noise parameter ϵ is normally distributed:

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

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

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

where

$$P = \{\mathbf{x} \in \mathbb{R}^d \mid l_i \leq x_i \leq u_i \forall i = 1..d\} \quad (5)$$

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. to the length of the robot program.

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

$$\min_{\mathbf{x}_1 \in P_1} E(\mathbf{x}_1) + \dots + \min_{\mathbf{x}_N \in P_N} E(\mathbf{x}_N) \quad (6)$$

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 industrial robots 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 pre-process 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], [14]. However, the acquisition frequency is limited by the monitoring hardware limitations.

Once the data is acquired, it needs to be resampled to match timestamps and stored in local storage. The energy data is usually recorded in regular timestamps, which results in time-series data. There are special database solutions for storing time-series data, such as InfluxDB. Also, 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 values (CSV) 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 optimisation algorithms. However, the nature of the black-box models prevents using first-order 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, optimization of energy consumption of robotic manufacturing systems should be data-efficient because every experiment 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, "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 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 IR. If the new parameters yield less energy consumption, they are kept; otherwise, the previous best parameters are reverted.

Another feature of the OMECO is exploration-and-exploitation which helps run the optimization only at some production cycles. This feature of the algorithm is controlled 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 10th iteration.

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

The OMECO algorithm accepts the following input parameters:

- \mathbf{x}_0 : an initial parameters guess either chosen randomly or using the human operator's knowledge;

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}

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1:  $y_0 \leftarrow E(\mathbf{x}_0)$  ▷ Measure energy consumption
2:  $y_{best} \leftarrow y_0$  ▷ Best energy consumption
3:  $\mathbf{x}_{best} \leftarrow \mathbf{x}_0$ 
4:  $\mathcal{D} \leftarrow \{(\mathbf{x}_0, y_0)\}$  ▷ Set the initial dataset
5:  $i \leftarrow 1$ 
6: while  $i < n$  do
7:   Sample  $p$  from uniform distribution  $U(0, 1)$ 
8:   if  $p \leq \alpha$  then
9:      $i \leftarrow i + 1$ 
10:     $\mathbf{x}_i \leftarrow \Phi(i, \mathbf{l}, \mathbf{u}, \mathcal{D})$  ▷ Call the optimization step
11:     $y_i \leftarrow E(\mathbf{x}_i)$ 
12:     $\mathcal{D} \leftarrow \mathcal{D} \cup \{(\mathbf{x}_i, y_i)\}$  ▷ Extend the dataset
13:    if  $y_i < y_{best}$  then
14:       $\mathbf{x}_{best} \leftarrow \mathbf{x}_i$ 
15:       $y_{best} \leftarrow y_i$ 
16:    end if
17:  end if
18: end while
19: return  $\mathbf{x}_{best}, y_{best}, \mathcal{D}$ 

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- \mathbf{l} : the lower bound of \mathbf{x}_0 ;
- \mathbf{u} : the upper bound of \mathbf{x}_0 ;
- n : the total number of optimization steps;
- α : the exploration parameter. This parameter controls how often the optimization should be performed.
- Φ : an application-dependant 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 processes 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 industrial robot 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.

The second experiment involves a more complex industrial bin-picking application where the movements are not pre-programmed 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.

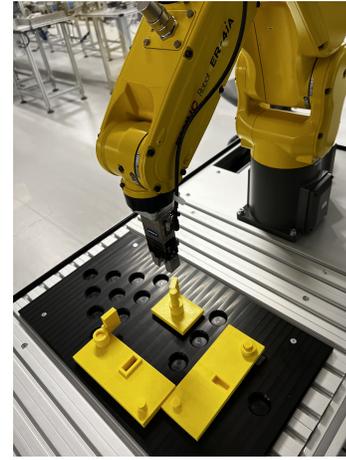


Fig. 2: Experiment setup representing a common pick-and-place operation in a robotic manufacturing.

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-4iA 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 below operations:

- **M1**. Move to the “pick approach” pose.
- **G1**. Open the gripper.
- **M2**. Move to the “pick” pose.
- **G3**. Close the gripper.
- **M3**. Move to the “pick retract” pose.
- **M4**. Move to the “place approach” pose.
- **M5**. Move to the “place” pose.
- **G3**. Open the gripper.
- **M6**. Move to the “place retract” pose.
- **M7**. Move to the “home” pose.

The labels M and G refer to different types of actions, and there are 7 motions labeled as M and 3 gripping actions 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 7 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 seconds 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 3D-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.

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 * 50 = 2500
Motion 2	[5, 40]	[5, 40]	35 * 35 = 1225
Motion 3	[5, 40]	[5, 40]	35 * 35 = 1225
Motion 4	[50, 100]	[50, 100]	50 * 50 = 2500
Motion 5	[5, 40]	[5, 40]	35 * 35 = 1225
Motion 6	[50, 100]	[50, 100]	50 * 50 = 2500
Motion 7	[50, 100]	[50, 100]	50 * 50 = 2500

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 below:

- 1) In the first step, the energy data was obtained through a FANUC robot controller. The instantaneous power data was collected every 50 milliseconds because of the limitations of the robot controller and network latency. The energy data was resampled to match the timestamps 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 pre-defined total number of iterations.

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

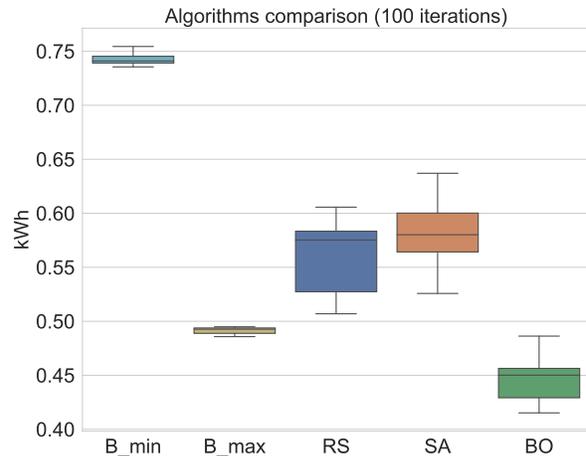


Fig. 3: Comparing algorithms.

2) *Experiment results:* To benchmark with the proposed ECO methodology, as a baseline, we measured the energy consumption of the robot with minimum and maximum allowed parameters configuration for the above-described pick-and-place process. For simplicity, we call the minimum allowed parameters configuration B_{\min} and the maximum allowed parameters configuration B_{\max} . Since the energy consumption measurement is noisy, we performed the same pick-and-place process 10 times for each configuration.

Random Search, Simulated Annealing, and Bayesian Optimization are non-deterministic algorithms, meaning their output will differ in every run even with the same set of input parameters. Therefore, each algorithm was run for 100 iterations 10 times for a fair comparison. The box plots and corresponding statistics are shown in Fig. 3 and Table II, respectively.

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

TABLE II: Experiment statistics. Values are in kWh.

Method	Min.	Max.	Median	Mean	Std.
B_{\min}	0.736	0.754	0.741	0.743	0.006
B_{\max}	0.486	0.495	0.493	0.491	0.003
Simulated Annealing	0.507	0.606	0.575	0.559	0.033
Random Search	0.526	0.637	0.580	0.579	0.033
Bayesian Optimization	0.415	0.486	0.450	0.446	0.020

From Fig. 3 and Table II, we can see that all optimization algorithms outperform the B_{\min} baseline. However, only the Bayesian Optimization outperforms the B_{\max} . The Bayesian Optimization outperforms B_{\max} on average by 9%, and the worst case of Bayesian Optimization 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 parameters 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.

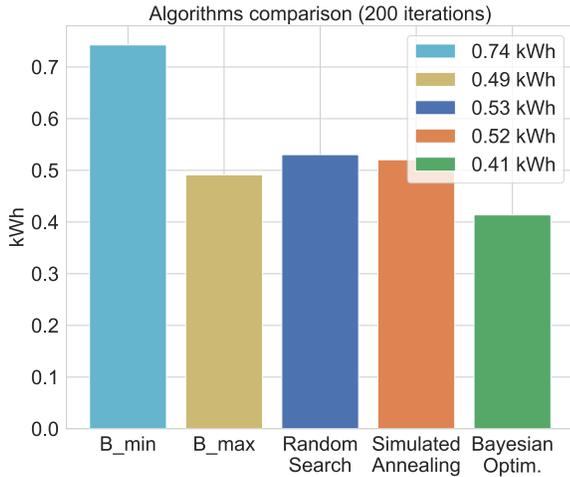


Fig. 4: The ECO results for pick-and-place process.

We can observe from Fig. 4 that Random Search, Simulated Annealing, and Bayesian Optimization outperform the B_{\min} by 28.38%, 29.73%, and 44.59%, respectively. However, Random Search and Simulated Annealing methods do not outperform the B_{\max} because usually, Random Search and Simulated Annealing methods require thousands of iterations to find the optimal solution. The Bayesian Optimization outperforms the 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 non-linear relationship between operating parameters and energy consumption.

TABLE III: Optimized velocity and acceleration values. This table shows velocity (v.) and acceleration (a.) values found by three optimization algorithms: Random Search (RS), Simulated Annealing (SA), Bayesian Optimization (BO).

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

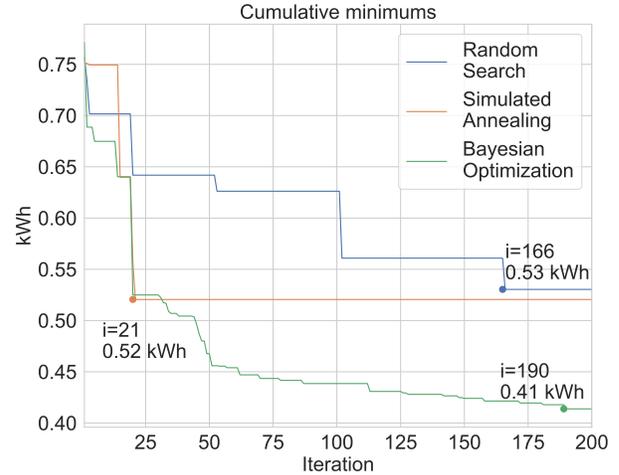


Fig. 5: The cumulative minimum values for three different optimization results.

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 Simulated Annealing algorithm finds its solution in 21 iterations. However, the algorithm fails to improve at all after that. The Random Search algorithm finds its best solution in 166 iterations. However, the found solution is not better than the solution found by the Simulated Annealing algorithm. The Bayesian Optimization finds its best solution in 190 iterations. However, after 30 iterations, it outperforms the Simulated Annealing algorithm, and after 40 iterations, it outperforms all the baselines. Consequently, it can be concluded that Bayesian Optimization is a relatively data-efficient algorithm.

The most efficient methods for energy consumption of IRs in the literature are work by [15] which required 729 samples, and work by [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*: Figure 6 shows the energy consumption outcome as a function of velocity and acceleration parameters. The left figure shows the energy consumption when all parameters are fixed except the velocity parameter of motion M7. One can observe that the relationship between velocity and energy consumption is non-linear, i.e., the minimum energy consumption is achieved when the velocity is around 70%. Similarly, the right sub-figure shows the energy consumption as a function of the acceleration parameter of motion M7. The non-linearity property also holds for this parameter. Figure 7 shows the contour plot of energy consumption as a function of velocity and acceleration parameters together. This

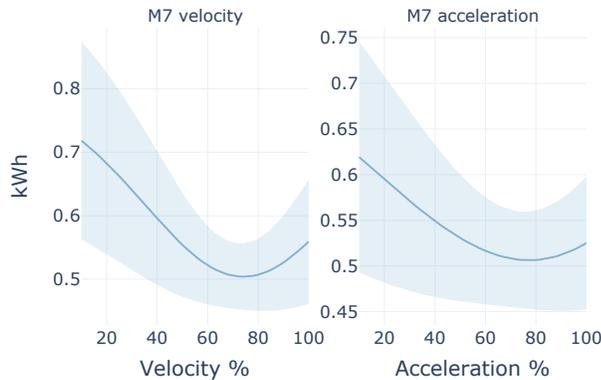


Fig. 6: Slice plot for motion 7. (Left) Velocity varies, other parameters are fixed. (Right) Acceleration varies, others are fixed.

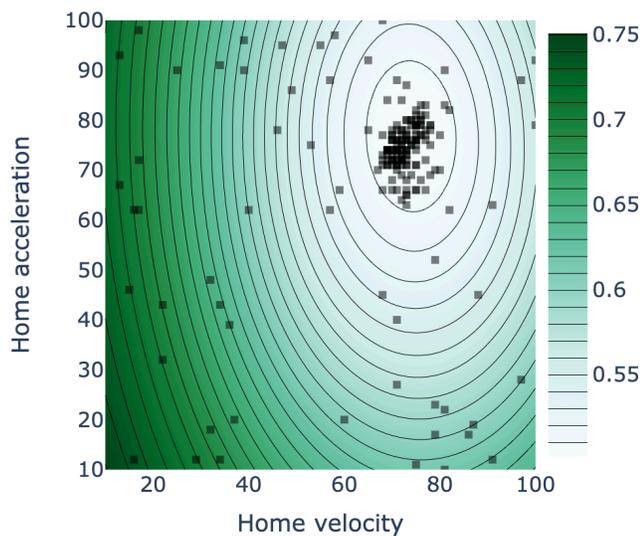


Fig. 7: Contour plot for motion M7 as a function of velocity and acceleration. Other parameters are fixed.

plot also reveals how the Bayesian Optimization reaches the optimal point. Initially, parameters are sampled from different regions. However, as the optimization progresses, more and more parameters are sampled in the neighbourhood 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 Figure 8). The objective of the process is to pick the parts and place them in their corresponding containers.

The picking of each object involves 7 different motions, but the parameters for these motions differ for each object, with different lower and upper bounds. Additionally, the robot must stop and select the next object to pick after each pick-and-

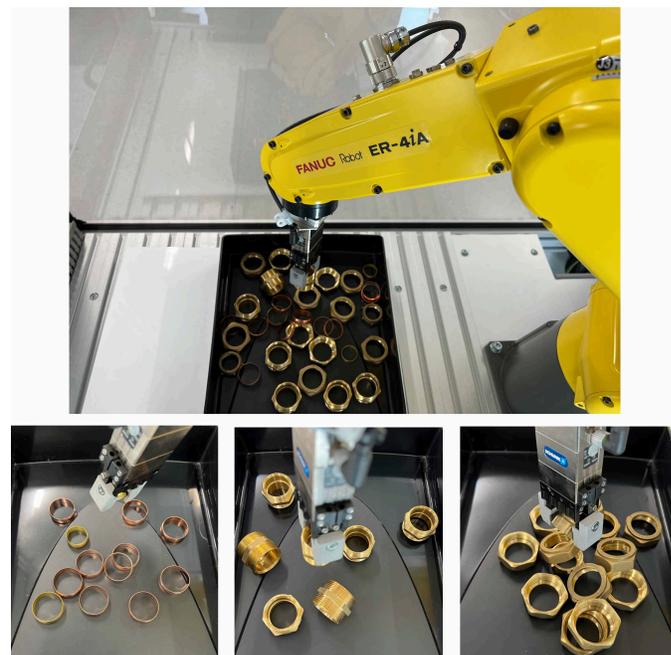


Fig. 8: The bin consists of three different parts with variable shapes and weights. The task is to sort the parts in their respective containers.

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 Bayesian optimization decreases. To address this issue, we performed two scenarios for optimizing energy consumption. In the first scenario, we optimized all 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.

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 Figure 9.

In the bin-picking experiment, the learning curves presented in Figure 9 reveal that the combined optimization approach did not yield better results than 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 opti-

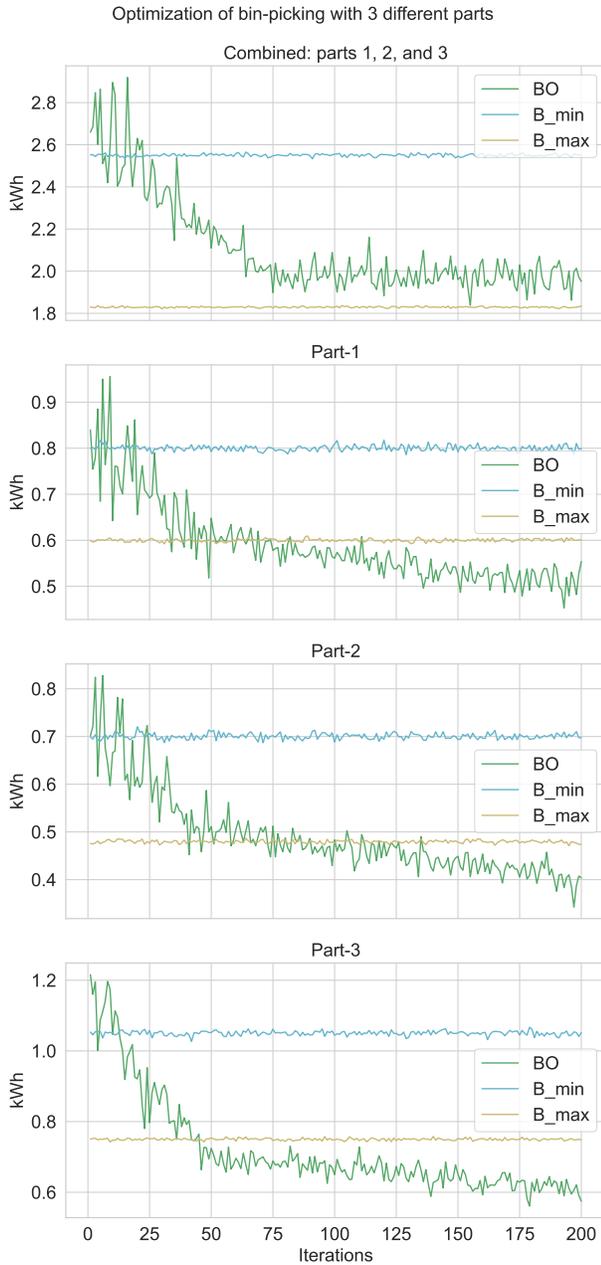


Fig. 9: The plot shows the optimization results of bin-picking for three different parts separately and the combined optimization.

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

C. Experiment 3: Optimization of drilling

In this aerospace manufacturing experiment, a FANUC M800iA robot controller and a drilling end effector controlled by a CNC machine were utilized to optimize the energy-

Comparison	Energy Savings
Individual vs. B_{min}	45.88%
Individual vs. B_{max}	25.00%
Individual vs. Combined	26.20%

TABLE IV: Energy savings comparison for bin picking experiment

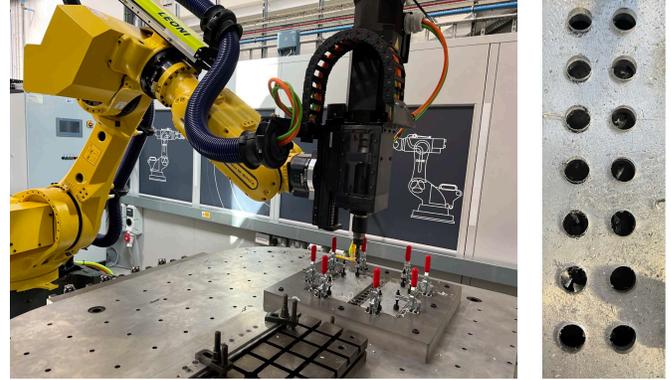


Fig. 10: Optimization of drilling. The aim is to energy efficiently drill holes through 6mm thick aluminium and 6mm thick cast acrylic layers.

efficient drilling of holes through 6mm thick aluminium and 6mm thick cast acrylic layers. The experimental setup is illustrated in Figure 10. The robotic arm's approach and retract positions were fixed, and the total drilling time was constrained to be within 20 seconds. The maximum allowed spindle speed was set to vary between 1500 and 2500 rpm, while the feed rate ranged from 150 to 180 mm/min as shown in Table V.

Parameter	Range
Spindle speed	1500 - 2500 rpm
Feed rate	150 - 180 mm/min

TABLE V: Parameter ranges for the drilling experiment

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. Bayesian optimization 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 Bayesian optimization results is displayed in Figure 11, while Figure 12 presents the slice plots of energy consumption in relation to spindle speed and feed rate parameters. These results 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.

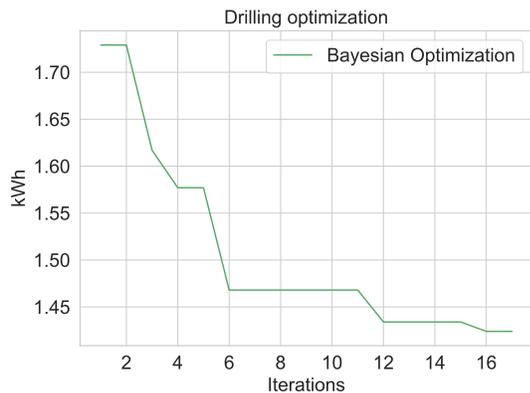


Fig. 11: The cumulative minimum values for drilling optimization results.

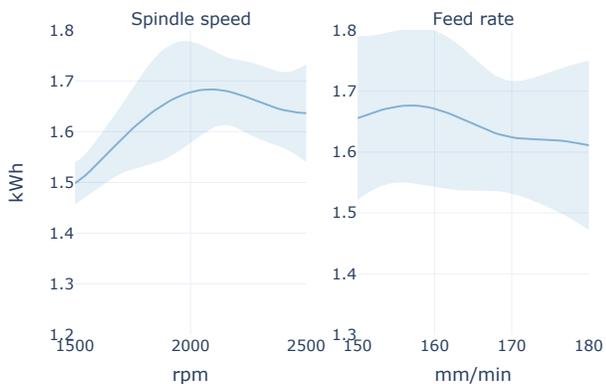


Fig. 12: Slice plot for drilling. (Left) Spindle speed varies, and the feed rate is fixed. (Right) The feed rate varies, spindle speed is fixed.

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

VI. CONCLUSIONS

In this work, we examined software-based energy consumption optimization for industrial robots and introduced a novel, modular, and prescriptive optimization methodology. This methodology treats the industrial robot and manufacturing process as a black-box model and is resilient to measurement noise. Our analysis corroborates the non-linear relationship between energy consumption and industrial robot operation, as previously demonstrated by other researchers. However, our approach uniquely enables online optimization of operating parameters without requiring extensive data.

Our experiments illustrate the applicability of this proposed method for optimizing robotic manufacturing processes using black-box optimization algorithms. Furthermore, the results from the second scenario indicate that optimization can be divided into sub-problems 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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