Idle Duration Prediction for Manufacturing System Using a Gaussian Mixture Model Integrated Neural Network for Energy Efficiency Improvement

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***Abstract*— Manufacturing activities dominate the energy consumption and greenhouse emissions of the industrial sector. With the increasing concerns of greenhouse gas (GHG) emissions and climate change in recent years, the significance of the performance in terms of sustainability of manufacturing has been gradually recognized by both academia and industry. Various researches have been implemented to analyze, model, and reduce the energy consumption of manufacturing activities toward sustainable manufacturing. In a typical manufacturing system with multiple machines and buffers, the state of a certain machine is not only determined by the machine itself, but also the states of the adjacent machines and buffers. Therefore, machines may be in idle states due to nonincoming part from the upstream section of the manufacturing system or noncapacity to hold the delivered part to the downstream section of the manufacturing system. Those idle machines consume energy without production if there is no appropriate energy control strategy. In this article, we focus on the reduction of the energy waste for those idle machines in a typical multi-machine and multi-buffer manufacturing system. A Gaussian mixture model (GMM) integrated neural network is proposed to predict the duration of the idle periods for the idle machines, during which optimal energy control action can be identified and implemented under the constraint of production throughput of the manufacturing system. A manufacturing system simulator is built to provide the training dataset including the information, such as production throughput, energy consumption, buffer content, and failure rate, to the proposed neural network. A numerical case study for a five-machine-and-four-buffer manufacturing system is conducted to validate the effectiveness of the proposed prediction model in terms of the energy waste reduction for the idle machines.**

***Note to Practitioners*—This article proposes a prediction model to forecast the idle duration of the manufacturing machines in a typical multi-machine and multi-buffer manufacturing system. With this predicted result, two concerns in energy control for the idle machine, i.e., throughput protection and energy consumption reduction, can be more accurately modeled in decision-making procedure. Optimal energy control actions under the constraints of throughput maintaining and energy saving can be identified and implemented considering different warmup energy consumption and warmup time of the machines to reduce the energy waste for those machines in idle states without any production and thus, improve the energy efficiency of the entire manufacturing system.**

***Index Terms*—Energy control, Gaussian mixture model (GMM), idle time prediction, manufacturing system, neural network.**

I. Introduction

WITH the increasing concern of environmental protection in the past decade, greenhouse gas (GHG) emissions and global warming have become vital issues to the sustainable development of our society. The significance of energy management toward sustainability in different areas, such as residential, commercial, transportation, and industrial sectors, has been widely recognized. Among different end-use sectors, the industrial sector is the largest energy consumer and GHG emitter in the U.S. as well as in the world. Fig. 1 illustrates the distribution of the U.S. energy consumption by end-use sectors in 2017 [1]. Approximately 30 quadrillion Btu of energy was consumed by the industrial sector, which accounts for about 32% of the total energy consumed in the country [2]. Manufacturing activities dominate industrial energy consumption and GHG emissions [3]. It has been reported that manufacturing is responsible for 90% of industrial energy consumption and 84% of energy-related industrial carbon dioxide (CO_2) emissions [4]. Therefore, energy efficiency improvement in manufacturing has been considered an effective way that can be helpful to achieve the target of sustainability.

A great deal of research that analyzes, models, and optimizes the energy efficiency in manufacturing has been reported. The demand management in production lines was investigated and quantified using elasticity measures [5]. The framework of energy-conscious production scheduling and control in discrete manufacturing was proposed [6].

Many existing literatures related to energy efficiency focus on either specific manufacturing processes or a single machine manufacturing system [7]–[10]. The energy efficiency of a single machine system was defined [7]. An experiment to model the machine tool efficiency and specific consumed energy based on cutting parameters has been conducted [8]. A simultaneous productivity/cost efficiency improvement and energy saving scheme were studied in a

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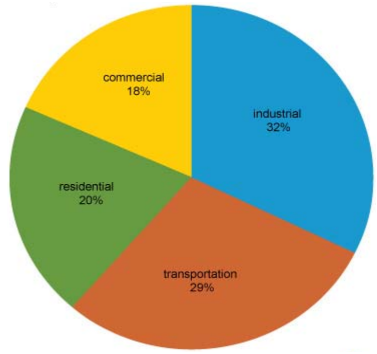

Fig. 1. U.S. end-use sector shares of total energy consumption, 2017 [1].

computer numerically controlled machining environment by experiments with different material removal rates [9]. The production schedule for a single machine was investigated using a greedy randomized adaptive search metaheuristic to minimize the total energy consumption and production tardiness [10].

Recently, the research of energy efficiency in manufacturing has also been extended from the level of a single machine or a certain process to the level of manufacturing system considering the interconnections between different machines and buffers in the system. For example, an energy-efficient production scheduling problem was formulated and the solution technique was proposed [11]. The opportunity window for energy saving of the machines in a manufacturing system was estimated considering the utilization of the work-in-progress parts in the downstream buffer locations [12]. A state-based real-time dynamic energy control for the idle (either blocked or starved) machines in manufacturing systems was proposed to reduce the energy waste using Markov decision process (MDP) [13]. In the MDP, the immediate energy consumption in the Bellman equation upon the given state and candidate energy control action is calculated directly. The subsequent energy consumption in the Bellman equation is approximately estimated by looking one-step ahead to address the computational concern for the proposed MDP in terms of "curse of dimensionality" so that the problem can be solved on a real-time basis.

In this article, we aim to simplify the modeling strategy and solution approach for real-time energy control for manufacturing system proposed in [13] resorting to a more accurate prediction tool to forecast the idle duration for those idle machines so that optimal energy control actions can be implemented under the constraints of energy saving and throughput maintaining.

The rest of this article is organized as follows. Section II introduces the background of the multi-machine manufacturing system and the essentials of blockage and starvation. Section III proposes a Gaussian mixture model (GMM) enhanced neural network to predict the duration of blockage and starvation upon its detection. Section IV implements a case study based on a section of an autoassembly system to illustrate the superiority in terms of energy waste reduction compared to the previous model proposed in [13]. Section V concludes this article and discusses future work.

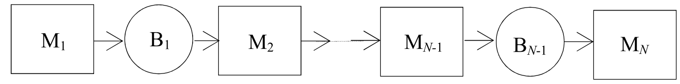

Fig. 2. Typical manufacturing system with N machines and $N-1$ buffers.

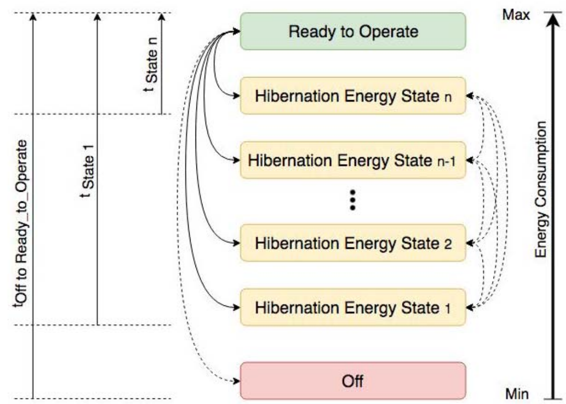

Fig. 3. Hibernation energy states.

II. Research Challenges in Energy Control for Multi-Machine Manufacturing System

A typical manufacturing system consists of N machines and $N-1$ buffers that are sequentially deployed as shown in Fig. 2, where the rectangles denote the machines and the circles denote the buffers.

For a typical manufacturing system that consists of multiple machines and buffers as shown in Fig. 2, both machines and buffers are deployed according to a certain sequence. Due to the random failures of the machines and finite capacities of the buffers, the operation state of a certain machine is determined not only by itself but also by its adjacent machines and buffers. For example, if machine M_{i-1} is down and buffer B_{i-1} is empty, then M_i is starved due to nonincoming parts from the upstream machines although machine M_i does not fail. Similarly, machine M_i can be blocked when machine M_{i+1} is down and buffer B_i is full. Either blocked or starved machine is in the idle state without producing any parts, while the energy state of such idle machine is still kept at the level of "ready for operation." If there is no additional appropriate control strategy to be implemented, the energy is wasted for those machines during the idle periods.

The idea of multiple energy states between "ready for operation" state and "OFF" state has been proposed [5], which indicates that the energy state of the idle machines could be adjusted to a certain "hibernation" level with the partial power consumption between "OFF" and "ready for operation" as shown in Fig. 3.

Due to the existence of warmup energy and warmup time when the machine energy state is adjusted from a lower level back to "ready for operation" as well as the uncertainty of the idle period, a deeper hibernation for the idle machine (e.g., turn off the machine) may not necessarily lead to a final energy saving. The energy saving resulted from a hibernation state for a short period may be offset by the warmup energy consumption while the idle machine is wakened up when it is not blocked or starved. Fig. 4 shows such an example.

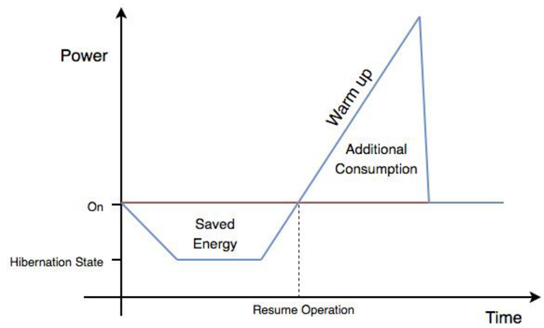

Fig. 4. Additional energy consumption due to a higher warmup energy and a shorter idle period.

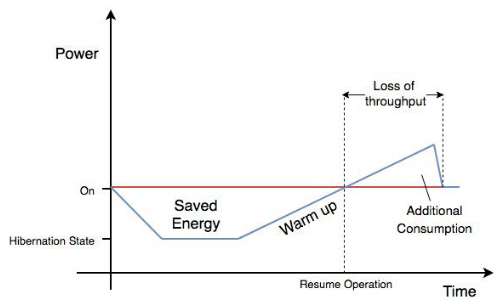

Fig. 5. Throughput loss due to long wakeup time.

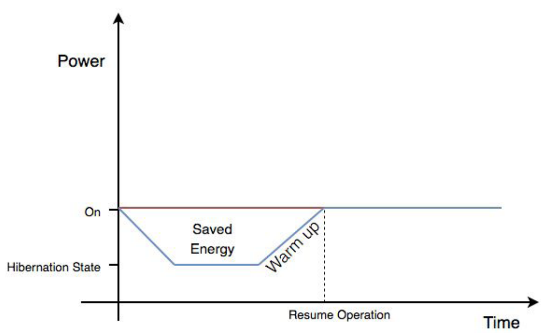

Fig. 6. Example of energy control with a 100% accurate idle duration prediction.

In addition, the production throughput is typically considered the first priority by manufacturers; the energy-saving actions should not sacrifice the production throughput. If the machine needs to take a longer time to resume its power level back to "ready for operation" from a certain hibernation level, the production will be influenced compared to the strategy of leaving alone since the production is further delayed even the idle status is ended. Fig. 5 shows such an example.

It can be seen that the ideal situation is to adjust the energy state to the lowest level so that it can be adjusted back to ready for operation exactly at the time point that the idle machine can resume operation as shown in Fig. 6. It implies an accurate estimation of the idle duration is needed when the idle machine is detected.

However, it is not easy to offer an accurate estimation for the idle period. On the one hand, an overestimation of idle duration may lead to a deeper hibernation state which requires a longer wake-up time and higher warmup energy consumption to resume to the "ready for operation" state. Additional energy may be consumed during the wakeup period when the machine resumes its operation earlier than the predicted time and the production throughput may be influenced. On the other hand, an underestimation may fail to capture the wasted energy as much as possible. A shallow hibernation state may be identified, and the machine may resume its energy state of "ready for operation" before it resumes operation.

The modeling strategy proposed in [13] bypassed the challenge of inaccurate idle period prediction through employing a traditional exponential smoothing perdition tool and considering the uncertainties by looking one step ahead. Specifically, the immediate energy consumption in the Bellman equation is calculated based on the given state and the candidate energy control actions. The candidate energy control actions are constrained by the predicted duration of idle time using exponential smoothing such that the time required for energy state adjustment is not larger than the predicted time, and energy consumption after adjustment is less than the action of leaving alone for the predicted idle period. The subsequent cost in the Bellman equation is approximately estimated by looking one step ahead. Three possible state variations at time $t + 1$ for those idle machines that are detected at time t are considered along with the respective probabilities and energy consumption to the end to estimate the expected value of the subsequent energy consumption.

The limitation of this method is complex as well as the uncertainties between overestimation and underestimation. In this article, we follow a more straightforward pathway, proposing a prediction tool that can offer the forecast of idle duration that is more close to the actual value, to address the challenges of real-time energy control for typical manufacturing systems with multiple machines and buffers. The details of the proposed model are introduced in Section III.

III. Proposed Model

In this section, a GMM integrated neural network is proposed to predict the idle duration for the idle machines in the manufacturing system. The optimal energy control actions (i.e., the optimal hibernation state) can thus be identified based on the predicted idle duration.

A. Manufacturing System Simulator

To obtain the dataset for training the proposed GMM integrated neural network model (see details in Section III-B), a manufacturing system simulator that can simulate a typical manufacturing system with multiple machines and buffers is built and used in this work.

In this simulator, three interconnected modules, an energy profile module, a production module, and an energy control module, have been built, respectively, and integrated as shown in Fig. 7.

The energy profile module defines the energy consumption profiles for each machine at different states as well as the time required for warmup. The production module defines the logistic relationship between the machines and buffers

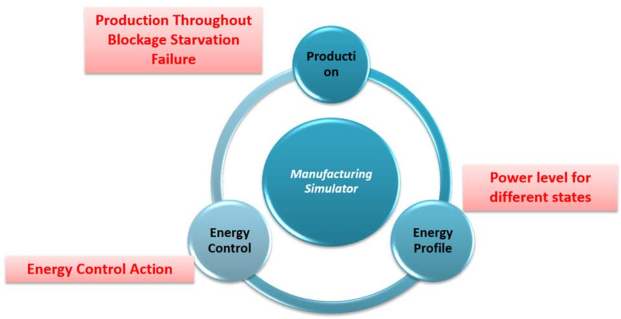

Fig. 7. Integration of three modules in the manufacturing system simulator.

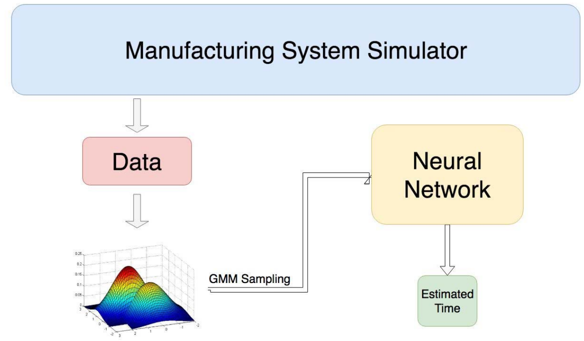

Fig. 8. Framework of the proposed GMM sampling strategy.

involved in the manufacturing system. The cycle time of each machine and the capacity of each buffer are also specified by this module. The energy control module defines the energy control actions that can be used for idle machines.

With the integration of the three modules, the typical behaviors, such as blockage and starvation, random failures, and repair, can be presented and the information with respect to the energy consumption, production throughput, machine state (operation, idle, or failure), and buffer state (the buffer content) can be presented and recorded. The energy control actions identified by the method introduced in Section III-C based on the predicted idle duration can be implemented.

B. GMM-Integrated Neural Network Prediction Model

A four-layer neural network model is proposed to learn and estimate the duration of each starvation/blockage event for every individual machine. Mean squared error is used as the loss function and Adam optimizer is used to update the model.

To expedite the learning process without losing convergence, instead of using random sampling method for training, a GMM is first trained on the training data and then high-likelihood data from the learned GMM are sampled for training. By using this sampling strategy, samples with higher likelihood of occurrence are emphasized during the training process, which in turn reduces estimator variance.

A GMM is composed of two main types of parameters, the component weight of each component and the mean and covariance of each component. For a GMM with C components, the cth component has a mean of μ_c and a covariance of Σ_c. The weight of each component c is defined as Φ_c. The probability distribution function is formulated by the following equation:

$$(x|\mu_c, \Sigma_c) = \frac{1}{\sqrt{(2\pi)^C |\Sigma_c|}} \exp\left(-\frac{1}{2}(x-\mu_c)^T \Sigma_c^{-1}(x-\mu_c)\right). \tag{1}$$

We aim to update the model parameters using maximum likelihood estimation techniques such that the likelihood of the observed data given the model parameters can be maximized. However, it is typically not practical to find the maximum likelihood solution for GMM by differentiating the equation and solving for zero. Thus, expectation–maximization (EM) algorithm, a numerical method for maximum likelihood estimation, is usually adopted to update GMM parameters. EM algorithm consists of two steps, expectation step and maximization step. In the expectation step, component labels are assigned to all data points given the model parameters Φ_c, μ_c, and Σ_c. The formula is shown in the following:

$$\gamma_{ic} = \frac{\phi_c N(x_i|\mu_c, \Sigma_c)}{\sum_{j=1}^{C} \phi_j N(x_i|\mu_j, \Sigma_j)} \tag{2}$$

where γ_{ic} is the probability that x_i belongs to component C_c. x_i will be assigned to the component that maximizes the probability.

The second step is the maximization step. In this step, it updates the model parameters to maximize the expectations of the component assignments in the expectation step

$$\phi_c = \sum_{i=1}^{N} \frac{\gamma_{ic}}{N} \tag{3}$$

$$\mu_c = \frac{\sum_{i=1}^{N} \gamma_{ic} x_i}{\sum_{i=1}^{N} \phi_{ic}} \tag{4}$$

$$\sigma_c = \frac{\sum_{i=1}^{N} \phi_{ic}(x_i - \mu_c)^2}{\sum_{i=1}^{N} \phi_{ic}}. \tag{5}$$

Those two steps are repeated iteratively until the algorithm converges. While sampling from the learned GMM, we perform the following steps.

1) Randomly select the Gaussian components according to the weight distributions.
2) Sample data point from the selected distribution according to the probability density function $N(x|\mu_s, \Sigma_s)$.

The framework of the proposed GMM integrated neural network prediction model is illustrated in Fig. 8.

C. Energy State Adjustment Based on the Prediction

Using the predicted idle duration based on the model proposed in Section III-B, the optimal hibernation energy state for the idle machine can be identified. Let ΔI_{ij} be the jth predicted idle time for machine i. The objective is to identify the optimal hibernation energy state q with power level of P_i^q for machine i so that the energy consumption during the predicted jth idle period can be minimized, which can be

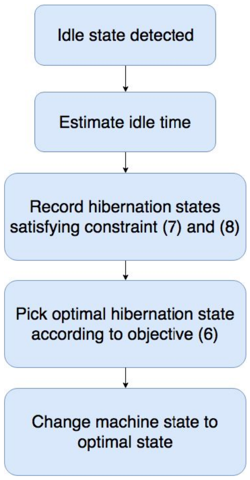

Fig. 9. Flowchart of identifying the optimal hibernation state for idle machines.

formulated by the following equation:

$$\min_{P_i^q} E_{ij} \tag{6}$$

where E_{ij} is the energy consumption of machine i during it jth idle.

The constraints are formulated by

$$\Delta I_{ij} \geq T_i^{Rq} + T_i^{qR}, \quad \forall q \tag{7}$$

$$\begin{aligned} P_i^R \times \Delta I_{ij} > P_i^q &\times \left(\Delta I_{ij} - T_i^{Rq} - T_i^{qR}\right) \\ &+ T_i^{Rq} P_i^{Rq} + T_i^{qR} P_i^{qR}, \quad \forall q. \end{aligned} \tag{8}$$

In (7), T_i^{Rq} is the time required by machine i for transiting its energy state from "ready for operation" level to a certain hibernation level q. T_i^{qR} is the time required by machine i for transiting its energy state from a certain hibernation level q to "ready for operation" level. Equation (7) shows that the predicted idle time should be no shorter than the required transition time between ready to operation state and the target hibernation state.

In (8), P_i^{Rq} is the average power of machine i when its energy state is transited from "ready for operation" to a certain hibernation level q. P_i^{qR} is the average power of machine i when its energy state is transited from a certain hibernation level q to "ready for operation" state. P_i^R is the power level of machine i when it is in "ready for operation" level. P_i^q is the power level of machine i when it is in a certain hibernation level q. Equation (8) shows that the energy consumption when energy state adjustment is implemented should be less than the energy consumption when idle machines are left alone.

The overall flowchart of the decision-making can be illustrated in Fig. 9.

IV. Case Study

In a case study, we consider a five-machine-four-buffer typical serial manufacturing system from a real autoassembly manufacturing system as shown in Fig. 10.

The productivity-related parameters in terms of mean time between failures (MTBFs) and mean time to repair (MTTR)

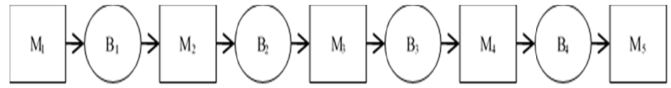

Fig. 10. Five-machine-four-buffer manufacturing system.

TABLE I
Machine Productivity-Related Parameters

Machine	MTBF (min)	Scale Parameter	Shape parameter	Cycle Time (min)	MTTR (min)
M1	100	111.39	1.5766	0.5	4.95
M2	45.6	51.1	1.6532	0.5	11.7
M3	98.8	110.9	1.7174	0.5	15.97
M4	217.5	239.1	1.421	0.5	27.28
M5	109.4	122.1	1.591	0.5	18.37

TABLE II
Machine Energy-Related Parameters

Machine	Power Level of R (kW)	Warmup Time (min)	Average power in warm up (kW)	Shutdown time (min)	Average power in shutdown (kW)
M1	21	1.4	25.2	0.5	5.2
M2	14	0.9	16.8	0.5	3.5
M3	20	1.35	24	0.5	5
M4	16	1.05	19.2	0.5	4
M5	13	0.85	1.2	0.5	3.25

TABLE III
Buffer Parameters

	B1	B2	B3	B4
Capacity	70	18	18	42
Initial Content	32	8	8	8

of each machine are illustrated Table I. The MTBF follows the Weibull distribution. The MTTR follows exponential distribution. The energy-related parameters, such as rated power, warmup power, warmup period, shutdown power, and shutdown period of each machine, are shown in Table II. The parameters of each buffer with respect to buffer capacity and initial content are illustrated in Table III. Three hibernation energy states with partial power consumption level of 50%, 30%, and 10% of "ready for operation" level are considered in this case.

The proposed manufacturing simulator is used for this five-machine-four-buffer manufacturing system to generate all the training data. The input data consist of 24-D state information of the whole manufacturing system during the time interval right before each blockage or starvation happens. A four-layer neural network is used. Dimensions of the four layers are 24, 24, 8, and 8, respectively, and ReLU function is used as the activation function for each layer.

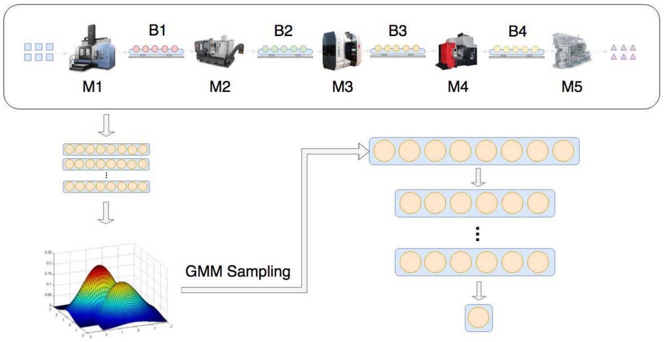

Fig. 11. Scheme of the case study.

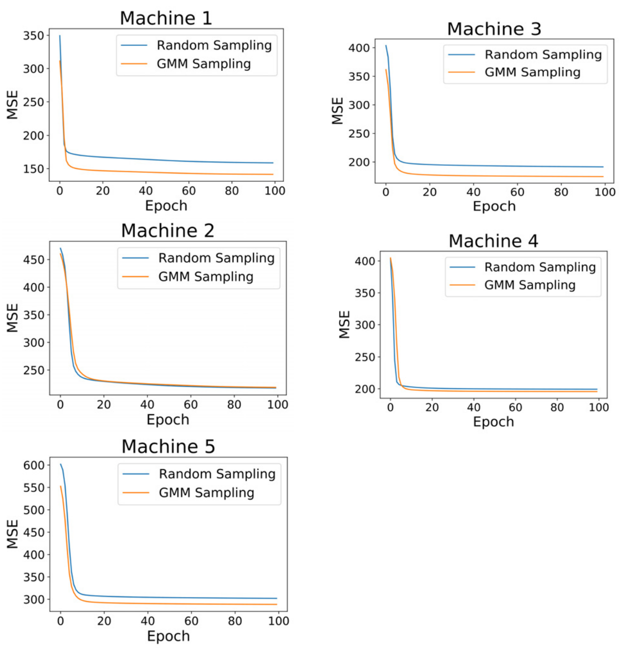

Fig. 12. Convergence comparison of the neural network with and without GMM sampling.

Specifically, we record the switch status, ONtime since last failure, current starvation time, current blockage time, current repair time for each machine, and amount of storage for each buffer. The corresponding training label is the real idle time of each starvation/blockage event. The learning rate is 0.0001. The scheme of the case study is shown in Fig. 11.

In the experiments, the simulator was run for 100 000 000 cycles and obtain a total of 1 384 517, 427 806, 894 657, 984 731, and 711 665 training samples for each of the five machines, respectively. We use a batch size of 4096 and update the models for 100 epochs. This neural network has been run both with and without the proposed GMM sampling strategy. The comparison of the convergence of the neural network with and without GMM is illustrated in Fig. 12. It can be seen, generally, when GMM is integrated, a faster convergence of the neural network parameter can be observed.

Using the predicted idle duration, the optimal energy state can be identified. An 8-h shift is run for this manufacturing system. The proposed idle prediction algorithm is integrated, and the optimal energy control action is identified using the predicted results following the decision-making procedure as shown in Fig. 9. The performance in terms of the energy waste after implementing the proposed neural network with and without GMM strategy is shown in Tables IV and V, respectively. The performance in terms of the energy waste by using the method in [13] is shown in Table VI. The comparison is summarized in Fig. 13.

It can be seen that there is no significant difference with respect to the system throughput since the overlap of 95% confidence interval. It can also be observed that the implementation of the energy control based on the proposed neural network prediction model can lead to a significant lower energy waste compared to an existing model based on MDP [13]. Further, with the employment of the proposed GMM sampling

TABLE IV

ENERGY WASTE (%) BY THE PROPOSED NEURAL NETWORK WITH GMM

Proposed neural network estimation with GMM		Throughput:	860±56
Machine	### Consumption (kWh)	### waste (kWh)	### Waste %
M1	165.16±3.54	0.3033±0.06	0.1895±0.04%
M2	105.65±2.44	0.1711±0.03	0.1660±0.03%
M3	151.31±3.47	0.3333±0.06	0.2244±0.04%
M4	121.09±2.90	0.2400±0.04	0.1996±0.03%
M5	98.149±2.38	0.2527±0.03	0.2625±0.04%
Total	641.38±14.6	1.3005±0.16	0.2073±0.02%

TABLE V

ENERGY WASTE (%) BY THE PROPOSED NEURAL NETWORK WITHOUT GMM

Proposed neural network estimation without GMM		Throughput:	860±62
Machine	Energy Consumption (kWh)	Energy waste (kWh)	Waste %
M1	162.70±4.35	0.4841±0.12	0.3024±0.08%
M2	103.78±2.97	0.1711±0.02	0.1678±0.03%
M3	148.85±4.22	0.3888±0.05	0.2647±0.04%
M4	118.82±3.40	0.2711±0.05	0.2299±0.05%
M5	95.801±2.66	0.2636±0.04	0.2778±0.05%
Total	629.97±17.4	1.5788±0.25	0.2543±0.02%

TABLE VI

ENERGY WASTE (%) BY THE EXISTING METHOD [13]

Existing method [13]		Throughput:	864±50
Machine	Energy consumption (kWh)	Energy waste (kWh)	Waste %
M1	166.89±3.05	2.2528±0.52	1.3886±0.34%
M2	106.62±2.22	1.0542±0.20	1.0118±0.22%
M3	153.13±2.99	2.6788±0.53	1.7862±0.38%
M4	121.79±2.71	1.2684±0.25	1.0478±0.21%
M5	99.410±1.93	1.1381±0.23	1.1777±0.26%
Total	647.86±15.5	8.392638889	1.3268±0.24%

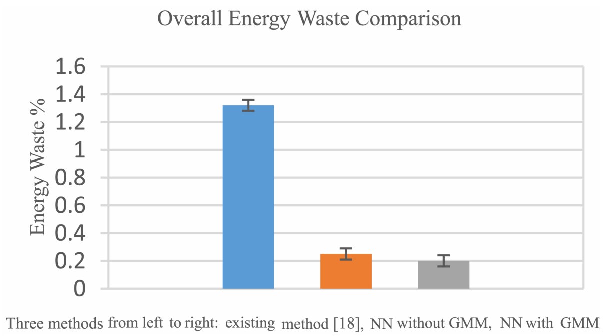

Fig. 13. Energy waste comparison after implementing three different energy control methods.

TABLE VII
BUFFER PARAMETERS OF A HIGHER INITIAL CONTENT

	B1	B2	B3	B4
Capacity	70	18	18	42
Initial Content	64	16	16	16

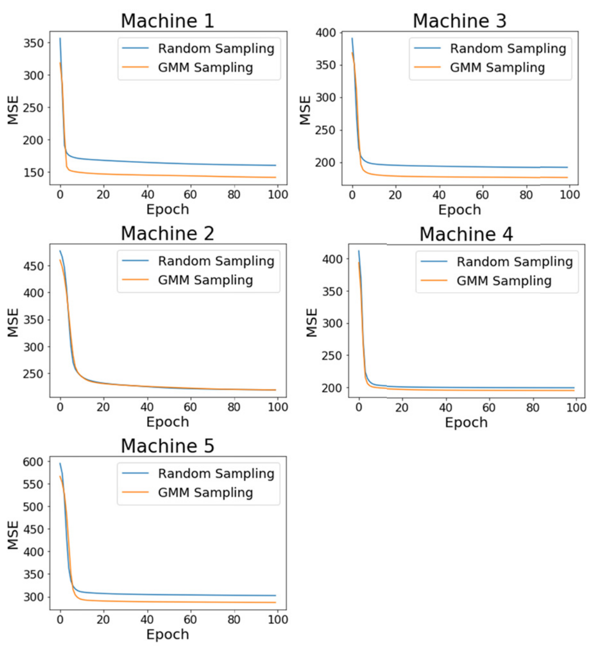

Fig. 14. Convergence comparison of the neural network with and without GMM sampling considering a higher initial buffer content.

TABLE VIII
ENERGY WASTE (%) BY THE PROPOSED NEURAL NETWORK WITH GMM CONSIDERING A HIGHER INITIAL BUFFER CONTENT

Proposed neural network estimation with GMM		Throughput:	860±56
Machine	### Consumption (kWh)	### waste (kWh)	### Waste %
M1	157.37±4.19	0.4608±0.06	0.2956±0.04%
M2	104.31±2.62	0.175±0.02	0.1708±0.03%
M3	150.76±3.64	0.3166±0.04	0.2132±0.03%
M4	121.81±3.05	0.2355±0.04	0.1938±0.03%
M5	99.321±2.50	0.1733±0.02	0.1741±0.02%
Total	633.59±41.83	1.36±0.39	0.21±0.02%

TABLE IX
ENERGY WASTE (%) BY THE PROPOSED NEURAL NETWORK WITHOUT GMM CONSIDERING A HIGHER INITIAL BUFFER CONTENT

Proposed neural network estimation without GMM		Throughput:	860±62
Machine	Energy Consumption (kWh)	Energy waste (kWh)	Waste %
M1	159.45±2.31	0.5949±0.09	0.3756±0.05%
M2	105.05±1.64	0.1944±0.03	0.1863±0.03%
M3	151.77±2.24	0.3722±0.06	0.2474±0.04%
M4	122.62±1.87	0.2844±0.04	0.2335±0.03%
M5	99.919±1.78	0.2347±0.04	0.2364±0.04%
Total	638.84±25.52	1.68±0.56	0.27±0.03%

TABLE X
ENERGY WASTE (%) BY THE EXISTING METHOD [13] CONSIDERING A HIGHER INITIAL BUFFER CONTENT

Existing method [13]		Throughput:	864±50
Machine	Energy consumption (kWh)	Energy waste (kWh)	Waste %
M1	156.79±9.76	4.0582±1.45	2.6494±0.42%
M2	103.46±6.90	1.5293±0.86	1.5257±0.36%
M3	150.02±9.95	3.0738±1.66	2.0976±0.46%
M4	120.66±8.46	1.6608±1.03	1.4019±0.36%
M5	98.33±6.87	0.9403±0.73	1.0015±0.32%
Total	629.26±41.16	11.26±4.39	1.86±0.04%

strategy, a significant lower energy waste percentage can be achieved when compared to the model without using GMM sampling strategy.

In addition, we double the parameters of the initial content in buffer locations to examine the model performance for this manufacturing system with a higher buffer content as shown in Table VII considering a possible situation when the work-in-process in the system is high. Same experimental settings and neural network parameters are used. The comparison of the convergence of the neural network with and without GMM is illustrated in Fig. 14. Similarly, when GMM is integrated, a faster convergence of the neural network parameter can be observed.

Similarly, use the predicted idle duration and follow the decision-making procedure as shown in Fig. 9; the energy control for idle machines is implemented. The performance in terms of the energy waste after implementing the proposed neural network with and without GMM strategy is shown in Tables VIII and IX, respectively. The performance in terms of the energy waste by using the method in [13] is shown in Table X. The comparison is summarized in Fig. 15.

Comparing Tables VIII–X with Tables IV–VI between two different initial work-in-process levels stored in buffer location

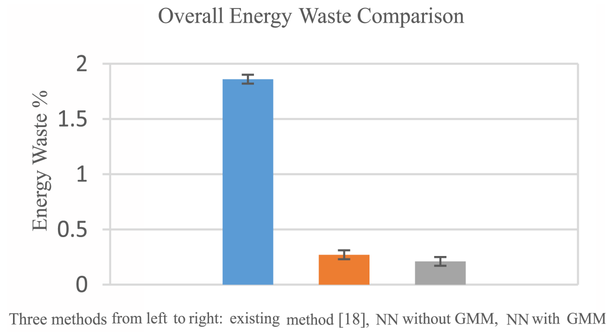

Fig. 15. Energy waste comparison after implementing three different energy control methods considering a higher initial buffer content.

of the manufacturing system, the proposed GMM integrated neural network prediction based energy control method can consistently outperform the existing method [13] in terms of energy waste reduction. The integration of GMM can also lead to a lower energy waste compared to the situation without GMM, which means that a more accurate prediction can be obtained.

V. Conclusion

In this article, a GMM integrated neural network prediction model is proposed to forecast the duration for the idle machines in a typical multi-machine and multi-buffer manufacturing system. Optimal actions in terms of energy state adjustment can be identified based on the predicted idle duration with the concerns of energy saving and throughput maintaining. The time required and energy consumed by the machines when switching its energy state from a lower level to the state of "ready for operation" are considered. A numerical case based on a five-machine-and-four-buffer production line from a real autoassembly system considering two different initial work-in-process part levels is used to verify the effectiveness of the proposed approach. Compared to an existing energy control method, the proposed method can catch more wasted energy during the idle period due to a higher accurate estimation of the idle duration.

For future work, we could further extend the model to analyze the sensitivity of the input information, i.e., predicted time length, machine warmup time/warmup energy, and machine reliability characteristics (MTTR and MTBF) to the final decisions. Hardware experimental verification could also be implemented to check the feasibility of the integration of the proposed method and existing control modules. The influence of the wide application of the proposed method to the nationwise policymaking can be further discussed. Furthermore, the effect and uncertainty from power (electricity supply) plant to manufacturing plant will also be investigated to understand the flow of energy consumption and reduce energy waste.

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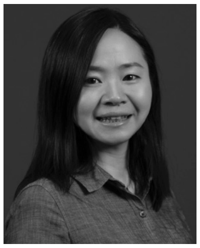

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