Data-Driven Real-Time Price-Based Demand Response for Industrial Facilities Energy Management

Renzhi Lu[a], Ruichang Bai[a], Yuan Huang[b,*], Yuting Li[c], Junhui Jiang[c], Yuemin Ding[d]

[a]*Key Laboratory of Image Processing and Intelligent Control, School of Artificial Intelligence and Automation, Huazhong University of Science and Technology, Wuhan 430074, China*
[b]*School of Information Engineering, Yangzhou University, Yangzhou 225127, China*
[c]*Department of Electronic Systems Engineering, Hanyang University, Ansan 15588, Korea*
[d]*Department of Energy and Process Engineering, Norwegian University of Science and Technology, Trondheim 7034, Norway*

Abstract

Recent advances in smart grid technologies have highlighted demand response (DR) as an important tool to alleviate electricity demand-supply mismatches. In this paper, a real-time price (RTP)-based DR algorithm is proposed for industrial facilities, aiming to minimize the electricity cost while satisfying production requirements. In particular, due to future price uncertainties, a data-driven approach is adopted to forecast the future unknown prices for supporting global time horizon optimization, which is realized by long short-term memory recurrent neural network (LSTM RNN). With the aid of predicted prices, the industrial facility energy management is formulated as a mixed integer linear programming (MILP) problem, which is then solved by Gurobi over a rolling horizon basis. Finally, an entire practical steel powder manufacturing process is selected as a case study to verify the RTP-based DR scheme. Numerical simulation results show that the proposed scheme is able to effectively shift energy consumption from peak to off-peak periods and reduce the electricity cost of the facility, while satisfying all of the operating constraints. The performance of the presented data-driven RTP forecasting approach is compared to different prediction methods, and error sensitivity analyses are also conducted to evaluate the impact of the RTP uncertainties and the robustness of the proposed RTP-based DR algorithm. Moreover, the DR capability to RTPs is investigated.

Keywords:
Data-driven price forecasting, long short-term memory, recurrent neural network, real time demand response, industrial facility energy management.

1. Introduction

Over the past few decades, there has been growing global concern over resource scarcity and climate change, since the energy consumption has increased by more than 25% in the last 20 years and a further 15.35% increase is expected by 2030 [1]. Among various energy consumers, the industrial requirement accounts significant percentage, i.e., for 50% of total power consumption on Earth, and 70% of the power requirement in China is due to industrial appliances, corresponding to more than 38% of direct and indirect greenhouse gas emissions [2]. This has pushed many politicians to develop new national energy management strategies. To achieve this target, demand response (DR) is a promising approach that motivates consumers with flexible loads to vary their energy consumption in response to dynamic electricity prices or other incentives [3]. As a key smart grid technology, DR can effectively balance the supply and demand of electricity in the power systems, thereby improving energy efficiency [4], reducing carbon emissions [5], lowering user costs and enhancing grid stability [6].

However, only a few studies to date have investigated the benefit and feasibility of industrial DR. For example, the work of [7] proposed a DR energy management scheme for industrial facilities based on day ahead prices (DAP), in which a part of the oxygen generation process is used to evaluate the DR scheme. The authors of [8] demonstrated an intelligent energy management framework with time of use (TOU) price-based DR capability for a section of a tire manufacturing facility. Similarly, another study in [9] established an electricity and natural gas driven production-scheduling model for a manufacturing system with 6 stations and 5 buffers under TOU prices. To some degree, all of these DR models focused on an incomplete manufacturing scenario and did not consider the operational sequence of different machines in the production line, which is not realistic in practice [10]. In one study [11], an energy management system (EMS) model for an oil refinery was built based on DAP to minimize the electricity consumption cost, where interdependencies in the operating constraints of the mass flow and steam demand were considered; however, the EMS model did not integrate storage units for intermediate materials. In addition, another two efforts have been devoted recently to discuss the design of industrial DR mechanisms, i.e., [12] introduced a multi-objective DR optimization model for

*Corresponding author
Email address: `hy4335657@hotmail.com` (Yuan Huang)

Nomenclature

Abbreviations

DR	demand response
RTP	real time price
LSTM	long short-term memory
RNN	recurrent neural network
MILP	mixed integer linear programming
DAP	day ahead price
TOU	time of use
EMS	energy management system
ANN	artificial neural network
ARIMA	autoregressive integrated moving average
FFNN	feed forward neural network
NSL	non-shiftable load
STL	shiftable load
CRL	controllable load
MAE	mean absolute error
MAPE	mean absolute percentage error
RMSE	root mean square error

Variables and Parameters

n	machine index
M_n	machine representation
B_n	buffer representation
p	operating point
h	hour index
$I^h_{n,p}$	status for operating point p of machine n in hour h
P	the total number of operating points
E^h_n	energy consumption of machine n in hour h
$e_{n,p}$	energy demand of machine n on operating point p
E^h	total energy consumption of all machines in hour h
N	the total number of working machines
$E^{\max}$	the maximum electricity that can be purchased
G^h_n	produced quantity of machine n
C^h_{n+1}	consumed quantity of machine $n+1$
$g_{n,p}$	production rate of machine n with operating state p
$c_{n+1,p}$	consumption rate of machine $n+1$ with operating state p
S^h_n	the storage of a buffer for machine n during hour h
$S^{\min}_n$	lower bound of buffer capacity
$S^{\max}_n$	upper bound of buffer capacity
π^h	real time price at hour h
π^τ	future price at hour τ
S^{tar}	the required final target production output
S^H_N	the total amount of final product
c_t	a separate hidden memory cell
f_t	the forget gate
i_t	the input gate
o_t	the output gate
W	the weight of each corresponding cell
b	the bias of each corresponding cell
π^τ_{for}	the forecasted price
π_{rea}	the actual price
K	the total number of samples
π_{err}	the prediction error
σ	standard deviation

labor- and energy-aware industrial production scheduling; [13] proposed a DR management scheme to promote the interaction between energy supply and demand for industrial systems. However, these two DR mechanisms were designed by deterministic models: that is, assuming next day electricity prices (e.g., TOU or DAP) are available to the facility, then the optimal energy consumption plan can be predefined accordingly by minimizing the daily costs or other objectives.

All the studies described above are based on the hypothesis that the electricity prices of the next day are known in advance. Once the optimal decisions have been determined, the industrial facilities are forced to follow that strategy, which is limited to fixed scheduling plans and does not allow a response to unexpected variation [14]. By contrast, real-time price (RTP) reflects the actual online conditions of the power grid more realistically, given the highly dynamic parameters associated with energy generation and price signal [15]. A comparison of DAP and RTP indicates that the high-resolution RTP will be of more benefit to power systems in terms of flattening the load profile and reducing peak demand [16]. Hence, it is imperative to devise innovative industrial DR algorithms that can accommodate the volatility and uncertainty of dynamic RTPs.

Several portable RTP-based DR energy management schemes have been proposed to help electricity users make timely decisions as a response to received RTPs, such as, [17] presented a DR algorithm for smart grid systems under RTPs, aiming at helping the utility company to purchase resources from its customers to balance energy fluctuations and enhance grid reliability; [18] designed a RTP based demand side management framework for microgrids to minimize operation cost and maintain power balance, considering the uncertainties of renewable energy profiles; [19] developed a RTP setting policies for DR consumers to produce desirable usage behaviors and flat demand curves, taking into account their characteristics with changing degrees of responsiveness to price adjustments at different time slots. However, these works were all designed for independent load scheduling or grid-level controlling. It is difficult to apply these DR schemes to industrial facilities directly, because an industrial manufacturing process is usually composed of different correlated and consecutive tasks that are inherently function together: different types of equipment in production lines must follow particular operational sequences [20]. Modeling DR problems in industrial sectors should capture the physical interactions of different machines, for instance, that a machine cannot start unless its feed is provided by the feeding machine [21]. A recent work [22] enabled industrial loads to fully achieve their potential as DR resources in the face of instantaneously varying RTPs, by utilizing an artificial neural network (ANN) model to predict future price signals. Although this work handled future uncertainties using the ANN method, the prediction errors pertaining to future unknown prices were not addressed. When using forecasting in electricity prices for DR energy management, it is important to note that there exist some errors in forecasting due to the uncertainty of weather information in energy generation and the randomness of user behaviors in energy consumption related to the electricity prices [23]. Therefore, the prediction errors should be considered when designing a DR scheme. Otherwise, the performance of the DR scheme will be not guaranteed because of the prediction errors [24]. In fact, the prediction errors existing in the future prices could potentially threaten the quality and robustness of the DR scheme [25].

Another critical issue is that although some previous work has been conducted on RTP-based DR, the price forecasting approaches in these studies used statistically based linear prediction methods, i.e., [26] introduced an autoregressive integrated moving average (ARIMA) model to the price forecasts, with the objective of helping electricity participants to submit corresponding DR strategies to maximize their profits; whereas the relationship between electricity price and its related factors is usually nonlinear [27]. The statistical methods forecast the price using a linear mathematical combination of previous prices and exogenous factors, such as historical demands, weather information, or fuel prices, which requires the analysis of a large amount of data and complex mathematical models; this increases the computational burden [28]. Recently, deep learning, a data-driven approach, has been utilized to address the uncertainties in price forecasting, and has been found to be capable of identifying complex nonlinear relationships perfectly between multiple inputs and outputs without acquiring previous knowledge or understanding physical processes [29]. The work of [30] presented a deep neural network based methodology to predict electricity prices and the performance performed better than statistic time-series models, such as the ARIMA model. Similarly, the authors in [31] proposed a deep learning based modeling framework for electricity price forecasting and verified how to improve the predictive accuracy. With more accurate electricity price forecasting, the DR schemes can efficiently manage the energy consumption of industrial facilities.

Given all the factors mentioned before, this work proposes an RTP-based DR scheme for industrial facilities to balance power fluctuation and enhance grid reliability. Specifically, to manage future price uncertainties, a framework based long short-term memory recurrent neural network (LSTM RNN), which is the latest and one of the most popular deep learning techniques, is adopted to both tackle the tricky price forecasting issue and support global real-time optimization. The proposed framework is tested on a real publicly available power grid data set, and the performance is comprehensively compared to various benchmarks including the state-of-the-art in the field of price prediction. The presented LSTM RNN approach is demonstrated to outperform the other rival methods. Furthermore, in cooperation with the forecasted future prices, the decision making procedure of RTP-based DR scheme is formulated as a mixed integer linear programming (MILP) problem, which is then solved using a Gurobi solver over a rolling horizon basis; the obtained solution yields optimal operation points for each industrial machine. Finally, case studies are carried out over an entire practical steel powder manufacturing process with different designed scenarios. The comparative cases articulate the advantages of the developed algorithms and their validity in terms of reducing electricity costs, mitigating peak demand, and improving grid reliability.

To highlight major differences of the proposed scheme with existing literatures, a comparative analysis is carried out with respect to 6 aspects as given in Table 1, including time horizon, application scenario, manufacturing process, electricity pricing, price forecasting technique and whether considering prediction errors or not. In summary, the main contributions of this paper are:

First, an innovative data-driven RTP-based DR scheme is proposed for industrial facilities energy management, wherein an entire practical steel powder manufacturing process is used to demonstrate the performance of the scheme.

Second, LSTM RNN is adopted to overcome future price uncertainties in presence of the rapidly updated RTPs, and several different price forecasting approaches are utilized to compare the performance.

Third, the decision making process of energy management scheme is formulated as a MILP problem by bridging current and future time slots together, which is then solved over a rolling horizon basis with the aid of the predicted prices.

Fourth, error sensitivity analyses are conducted to evaluate the impact of the RTP uncertainties, showing that the proposed RTP-based DR algorithm has good robustness towards prediction errors.

Fifth, the electricity cost with and without RTP-based DR are compared, indicating that the proposed DR scheme can reduce the electricity cost significantly, and the DR capability to RTPs is also investigated.

The remainder of this paper is organized as follows. Section 2 describes the problem formulation for industrial facilities, and the proposed RTP-based DR algorithm is introduced in Section

Table 1: Comparison of the Proposed Work with Other Literatures

References	Time Horizon	Application Scenario	Manufacturing Process	Electricity Pricing	Price Forecasting Technique	Considering Prediction Errors
Ref [7, 8, 9, 11, 12, 13]	day-ahead	industrial facility	incomplete	DAP/TOU	-	-
Ref [17, 18]	real-time	grid-level	-	RTP	deep neural network	no
Ref [19]	real-time	residential load	-	RTP	time series model	no
Ref [22]	real-time	industrial facility	entire	RTP	ANN	no
Ref [26]	-	-	-	-	ARIMA	no
Ref [30]	-	-	-	-	deep neural network	no
Ref [31]	-	-	-	-	deep learning	no
This work	real-time	industrial facility	entire	RTP	LSTM RNN	yes

Figure 1: A common industrial manufacturing process.

3. Case study results are reported and discussed in Section 4. Finally, Section 5 presents conclusions and future work.

2. Problem Formulation

In this section, a decision making problem is constructed for an industrial facility, which takes part in an RTP-based DR program. The facility is assumed to be equipped with an EMS that receives the RTP from the utility company periodically (1 h is used as an example time interval throughout this paper) and is responsible for managing the energy consumption of multiple devices with various characteristics. Fig. 1 shows a common industrial manufacturing process [32], where M_n and B_n represent the machine and buffer, used to produce the final goods and store the intermediate product, respectively. The mathematical formulations of the energy and production model and various operation constraints, as well as the objective function, are depicted in the next subsections.

2.1. Energy Model and Constraints

Industrial machines can be regarded as a complex of different consecutive electricity loads. According to their characteristics and priorities under different specific operating conditions, these loads are usually divided into three categories [33]: non-shiftable load (NSL; once it starts operation it must work continuously), shiftable load (STL; it has two operating states, "on" and "off"), and controllable load (CRL; it can work at different operating levels with different power demands). $I_{n,p}^h$ is a binary variable that indicates the status of operating point p for machine n during hour h. Thus, $I_{n,p}^h = 1$ if machine n is operated with operating point p, and $I_{n,p}^h = 0$ otherwise. Then, during 1 h, a machine can only be executed at one operating point, which is constrained as follows:

$$\sum_{p=1}^{P} I_{n,p}^h = 1 \tag{1}$$

where P is an integer representing the total number of operating points, i.e., $P = 1$ for NSL, $P = 2$ for STL, and $P \geq 3$ for CRL.

After choosing an operating point, the energy consumption of machine n during hour h is:

$$E_n^h = \sum_{p=1}^{P} I_{n,p}^h \cdot e_{n,p} \tag{2}$$

where $e_{n,p}$ indicates the energy demand of machine n at operating point p.

Thus, the total energy consumption of the entire manufacturing process during hour h is:

$$E^h = \sum_{n=1}^{N} E_n^h \tag{3}$$

where N denotes the total number of working machines in the production line.

For industrial facilities energy management, peak demand is generally considered as a critical factor, because many manufacturing processes are subject to maximum electricity consumption restrictions, as shown below:

$$E^h \leq E^{\max} \tag{4}$$

where $E^{\max}$ indicates the maximum electricity that can be purchased, constrained by physical limitations or a contract signed with the utility company [34].

2.2. Production Model and Constraints

During the manufacturing period, there is supposed to be a buffer between every two consecutive machines, which acts as storage to provide an opportunity for coordination between two different machines. As shown in Fig. 1, if the production rate of M_n is higher than the consumption rate of M_{n+1}, the surplus resources will be saved in the middle storage buffer B_n for future use. By contrast, if the production rate of M_n is lower than the consumption rate of M_{n+1}, the latter machine will enter the off mode until enough resources have been augmented in the storage. The material storage S_n^h of a buffer for machine n during hour h is calculated as follows:

$$S_n^h = S_n^{h-1} + G_n^h - C_{n+1}^h \tag{5}$$

$$G_n^h = \sum_{p=1}^{P} I_{n,p}^h \cdot g_{n,p} \tag{6}$$

$$C_{n+1}^h = \sum_{p=1}^{P} I_{n+1,p}^h \cdot c_{n+1,p} \tag{7}$$

where S_n^{h-1} is the storage at hour $h-1$, G_n^h (C_{n+1}^h) denotes the produced (consumed) material quantity of machine n ($n+1$), and $g_{n,p}$ ($c_{n+1,p}$) indicates the material production (consumption) rate of machine n ($n+1$) in operating point p.

During any hour, to satisfy the operation of processing machines, it is necessary to maintain a minimum amount of material flow. Moreover, the stored material cannot exceed a maximum capacity limitation. Therefore, S_n^h is constrained as follows:

$$S_n^{\min} \leq S_n^h \leq S_n^{\max} \tag{8}$$

2.3. Objective Function

For an industrial application, the objective is to minimize the energy cost of the whole time horizon while satisfying the production requirement. The total electricity cost includes the cost of the current slot (given the RTP π^h at hour h) and the aggregate cost of future slots (with the assumption of future prices $\pi^\tau, \pi^{\tau+1}, ..., \pi^H$, where $\tau = h+1$):

$$\min \left\{ E^h \cdot \pi^h + \sum_{\tau=h+1}^{H} \left(E^\tau \cdot \pi^\tau\right) \right\} \tag{9}$$

The reason for considering the remaining $H-h$ slots of the scheduling horizon is to maintain adaptability, as the consecutive electricity loads of an industrial manufacturing process are interdependent and cannot be treated independently. Using an extended scheduling horizon, the proposed model could avoid a possibly jumpy, unfeasible, and hard-to-implement solution [35].

It is also usually necessary to keep a minimum amount of final product when the scheduling horizon finishes. The required final target production output is denoted as S^{tar}, which should satisfy the following criteria:

$$S_N^H \geq S^{tar} \tag{10}$$

where S_N^H denotes the total amount of final product produced by the last machine N during the end hour H.

3. Real-Time Price-Based Demand Response Algorithm

As the proposed DR scheme is based on RTP, only one current price can be obtained at each hour. Thus, future price information is needed to minimize the global energy cost. This section contains the data-driven approach for price forecasting utilized to support the whole time horizon scheduling, and the automated DR algorithm used to minimize the electricity cost of the industrial facilities while satisfying the production requirement.

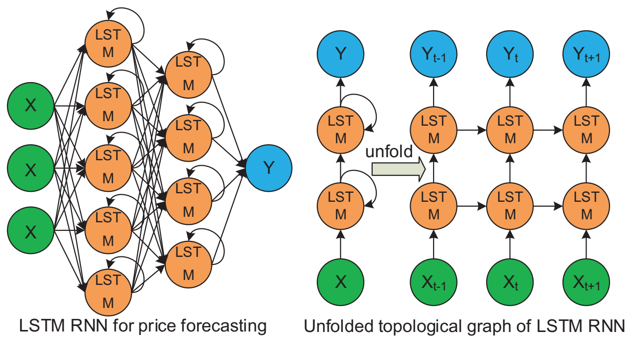

Figure 2: Long short-term memory recurrent neural network.

3.1. Data-Driven Price Forecasting

It should be mentioned that the objective function (9) in Section 2 is not formally defined because the $\pi^\tau, \pi^{\tau+1}, ..., \pi^H$ are unknown values. To manage this situation, a data-driven approach is adopted to handle the future price uncertainties, which is implemented by LSTM RNN, as shown in Fig. 2.

RNN is a kind of deep neural network that is good at processing sequence data. In contrast with a traditional neural network, RNN consists of a feedback loop, allowing the network to accept a sequence of inputs, where the outcome from step $t-1$ is fed back into the network to affect the output of step t, and so on for each succeeding step (left side of Fig. 2). RNN has a chain-like structure with repeating modules, for the purpose of utilizing these modules as a memory to save important information from previous processing steps (right side of Fig. 2). However, the information loops repeat, leading to huge updates to neurons, resulting in an unstable network when the input sequence is long, because of the accumulation error during the course of updating. This phenomenon is known as gradient exploding or vanishing [36], which makes it difficult to learn long-term dependencies within the time series. The LSTM network [37] illustrated in Fig. 3 was proposed to overcome this issue. LSTM is an efficient RNN architecture for time series forecasting. In addition to the internal hidden state h_t, it maintains a separate hidden memory cell c_t, to keep short-term information and long-term information, respectively. The LSTM network also includes three gating mechanisms to control the information flow throughout the learning procedure, which are the forget gate f_t, the input gate i_t, and the output gate o_t. With the assistance of these three gates, the memory cell c_t can forget, delete, and update internal information selectively, bringing about a better understanding of long-term dependencies in the sequences. The LSTM transition processes are updated as follows:

$$f_t = \sigma\left(W_f \left[h_{t-1}, X_t\right] + b_f\right) \tag{11}$$

$$i_t = \sigma\left(W_i \left[h_{t-1}, X_t\right] + b_i\right) \tag{12}$$

$$o_t = \sigma\left(W_o \left[h_{t-1}, X_t\right] + b_o\right) \tag{13}$$

$$g_t = \tanh\left(W_g \left[h_{t-1}, X_t\right] + b_g\right) \tag{14}$$

$$c_t = c_{t-1} \times f_t + i_t \times g_t \tag{15}$$

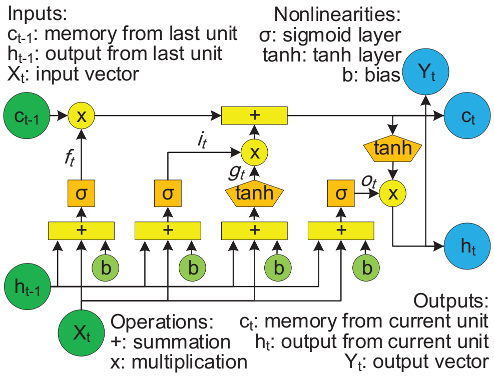

Figure 3: Long short-term memory network unit.

$$h_t = o_t \times \tanh(c_t) \tag{16}$$

All weights (W) and biases (b) of the corresponding cells stated in the above equations are learned by minimizing the gaps between the LSTM outputs and the actual values. Compared to the original RNN, LSTM RNN adaptively controls how much information flows through these gates. It is based on the idea of creating paths through time that have derivatives that neither vanish nor explode, and these cells accumulate information (such as evidence for a particular feature or category) over a long duration. Therefore, LSTM captures the long-distance dependencies among sequence data.

Since the quantity and quality of input features influence the forecasting performance, considerable efforts have been devoted towards the extraction and selection of inputs, based on methods such as correlation analyses and principle component analyses [38]. Generally, electricity price can be forecasted by evaluating a variety of features, i.e., electricity demand, generator supply, weather, temperature, calendar, and so forth [39]. An ideal electricity price forecasting model should include all the possible features that affect the final electricity price. However, in reality, it is impossible and unnecessary to include all those features [40]. For example, features of generator status, representing the current failure or operating mode of a generator, in many deregulated electricity markets are confidential information, and thus such data cannot be directly obtained online [41]. Moreover, the most important factor for a successful LSTM RNN learning is to find out a set of "fit" training data. Considering too much or too little related information will have a crucial impact on the prediction accuracy [42]. Specifically, during one LSTM RNN training process, if too few features are considered, there will be not sufficient samples to fit the training, and this is called underfitting. On the contrary, if too many features have been considered in the training data, the real valuable features are difficult to play a guiding role among the disturbances items, and this is called overfitting [43]. Both underfitting and overfitting will decrease the prediction accuracy.

In this work, we use widely accepted features: the dynamic energy demand and electricity price series in the previous three time intervals and the corresponding hour in each of the previous two days (i.e., 1, 2, 3 h earlier and the current hour, as well as 1 and 2 h earlier, from 1, 2 days prior); the varying current and lagged weather temperatures in the previous 3 h; and static calendar effects such as the hour of the day, day of the week, and holiday/non-holiday indicator. These features allow the LSTM RNN to capture both the correlations and variation in the price information. The output is the predicted price in the target time interval. To evaluate the performance of the forecasting approach, three widely used statistical indictors are selected to compare the predicted values with real values: the mean absolute error (MAE), mean absolute percentage error (MAPE) and root mean square error (RMSE).

$$MAE = \frac{1}{K}\sum_{k=1}^{K}\left|\pi_{for} - \pi_{rea}\right| \tag{17}$$

$$MAPE = \frac{1}{K}\sum_{k=1}^{K}\frac{\left|\pi_{for} - \pi_{rea}\right|}{\pi_{rea}} \times 100\% \tag{18}$$

$$RMSE = \sqrt{\frac{1}{K}\sum_{k=1}^{K}\left(\pi_{for} - \pi_{rea}\right)^2} \tag{19}$$

where π_{for} and π_{rea} are the forecasted and actual price; and K is the total number of samples.

Algorithm 1 Price forecasting with LSTM RNN

1: Collect historical dataset D from electricity market;
2: Clean and pre-process the dataset D;
3: Divide the dataset into training set D_{tr}, validation set D_{va} and testing set D_{te};
4: Initialize the training network parameters, i.e., network depth d, hidden units amount n and so on;
5: Set the maximum number M of epochs.
6: **for** $m = 1$ to M **do**
7: Build LSTM RNN with the initialized network parameters (d, n) on Tensorflow;
8: Train the LSTM RNN by minimizing the loss function with a stochastic gradient descent method on training data set D_{tr};
9: Evaluate the trained LSTM RNN performance on validation data set D_{va};
10: Early stop if the validation performance is not improved.
11: **end for**
12: Compute the MAE, MAPE and RMSE of the well-trained LSTM RNN on testing data set D_{te};
13: Compare forecasting performance with other prediction methods.

The detailed procedure of adopting LSTM RNN for price forecasting is given as Algorithm 1. The process starts with data preprocessing of the inputs, and in the data preparation stage, any non-number data are replaced by the average of the data at the same time period from 1 day ahead and 1 day later. After formulating the input and output data, the dataset is split into three parts for training, validation, and testing. Then the algorithm moves into the training stage, and the network is first built with configuration parameters, i.e., the network depth, number of hidden units, and input and output sequence size. After initiation, the network is trained using a stochastic gradient descent method with an adaptive learning rate to minimize the loss function until the performance stabilizes. In this training procedure, the maximum training epoch is defined, but an early stopping mechanism is also utilized to prevent the model from overfitting. Specifically, if the monitored validation loss does not drop any further, the training process should be terminated. Finally, the well-trained network is tested on the testing data set and the evaluation criteria are used to assess the predictive accuracy. The performance is also compared to several other price prediction methods.

3.2. Automatic Demand Response Algorithm

As we know, in practical terms, there will always be some mismatches between forecasted and actual values. Thus, the future price π^τ is calculated from the forecasted price π^τ_{for} plus the prediction error π_{err} [35]. In this way, the objective function (9) can be reformulated as follows:

$$\min \left\{ E^h \cdot \pi^h + \sum_{\tau=h+1}^{H} \left[E^\tau \cdot \left(\pi^\tau_{for} + \pi_{err} \right) \right] \right\} \tag{20}$$

where the prediction error is supposed to follow a Gaussian distribution $\pi_{err} \sim N\left(0, \sigma^2\right)$, which has an expectation value of 0 and a standard deviation σ.

Based on the problem formulation and price forecasting described above, an automated RTP-based DR scheme is developed in Algorithm 2. At each hour h, the EMS receives the RTP from the utility company, and then updates the related inputs (i.e., the current hour h, the current electricity price and energy demand, and so forth), as well as utilizes the well-trained LSTM RNN to predict the prices for remaining $H - h$ hours. After obtaining the future forecasted prices, a new schedule for the entire industrial facility is generated. The objective function (20) together with the constraints of equations (1)-(8) and (10), are formulated into an MILP optimization problem that can be effectively solved using a commercial tool (i.e., Gurobi). The output consists of the optimal operating point for each machine, and the total minimum energy cost. It should be pointed out that the problem is optimized at each hour h to acquire energy consumption decisions for the current and remaining slots. However, only the decisions for the current hour are applied to the industrial loads, which provides the facility with optimal energy management instructions for the present slot. Then the horizon is shifted forward by one time step and the optimization is carried out anew. This process is repeated each time a new price is received until reaching the final hour H. Such an iterative procedure therefore enables the RTP-based DR scheme to be robust to measurement errors, missing information, and inaccurate forecasts, ensuring that the control policy dynamically adjusts and is self-correcting as new information arrives and changes in the operating environment occur.

In summary, this automated DR algorithm allows industrial facilities to both interact intelligently with the utility company in response to the RTP, and to generate dynamically optimized operating schedules for the machines, minimizing the electricity cost and meeting production requirements.

Algorithm 2 Automated DR with RTP

Input: the energy demand $e_{n,p}$ and production rate $g_{n,p}$ of all machines; the buffer capacity $\left[S_n^{\min}, S_n^{\max}\right]$; the target production output S^{tar}; the maximum purchased electricity $E^{\max}$; and the prediction error π_{err} related parameters, i.e., the standard deviation σ.

Output: the optimal operating point p of each machine, and the total minimum energy cost.

for h = 1 to H **do**
  Receive the RTP π^h for the current hour h;
  Update the inputs of LSTM RNN;
  Utilize the well-trained LSTM RNN (Algorithm 1) to predict future prices π^τ, $\pi^{\tau+1}$, ..., π^H;
  Formulate the objective Eq. (20) and constraint Eqs. (1-8, 10) into a MILP problem;
  Use a commercial tool to solve the optimization problem;
  Output the optimal solutions, i.e., the optimal operating point p for each machine;
  Only the decisions for the current hour will be executed.
end for

4. Case Studies And Numerical Results

This section presents case studies and numerical results to demonstrate the effectiveness of the proposed RTP-based DR scheme.

4.1. Case Configuration

4.1.1. Price Forecasting Setup

Realistic hourly power grid data on energy demands, electricity prices and temperature from PJM [44], as well as calendar information are collected to train and test the LSTM RNN. The data are split into three non-overlapping subsets for different purposes, namely, the training set (from January 1, 2019 to July 20, 2019), the validating set (from July 21, 2019 to August 24, 2019), and the testing set (August 25-31, 2019). The parameters of the LSTM RNN structure are as follows: the size of input layer is equal to the input data length with a value of 24; the number of hidden layers is set to 3 with a deeper architecture and each hidden layer has 40, 20, and 10 recurrent neurons, due to the fact that a network with more layers can obtain more compact representations of an input-output relationship [36, 37]; and the size of the output layer is 1, indicating the future price for next time step. The price forecasting simulations are carried out on hardware of a laboratory computer with 4 Intel Cores i5-2400, 3.10 GHz CPU, 16 GB RAM, and software in the Python environment with Tensorflow package. To train the network efficiently, the Adam optimizer with an adaptive learning rate is used to minimize the loss function. The maximum number of epochs is set to 200 and early stopping is employed to avoid overfitting during training and validation.

Table 2: Parameters of Different Loads

Name	Category	Operating point	Production rate	Energy demand	Buffer capacity
Reduction	NSL	on	15	75	100
Atomizer	STL	off	0	0	180
		on	30	60	
Dehydrator	STL	off	0	0	100
		on	15	10	
Dryer	STL	off	0	0	150
		on	15	30	
Separator	STL	off	0	0	100
		on	10	10	
Crusher	CRL	1	0	0	100
		2	10	15	
		3	15	20	
Classifier	CRL	1	0	0	150
		2	10	15	
		3	20	25	
Blender	CRL	1	0	0	200
		2	10	6	
		3	15	10	

Table 3: The Statistical Indicators of Different Approaches

Approaches	MAE	MAPE	RMSE
LSTM RNN	2.05	7.56%	7.29
FFNN	4.06	19.71%	8.03
ARIMA	5.82	34.67%	9.27

4.1.2. *Industrial Manufacturing Process*

An entire practical steel powder manufacturing process [45] is selected for the case study, as shown in Fig. 4, to illustrate the performance of the proposed RTP-based DR algorithm. From raw material (iron water) to final product (steel powder), the entire industrial manufacturing process includes 10 processes and 8 kinds of machines. According to the functionality and characteristics of each machine, they are classified into the three categories defined in Section 2, including one NSL (Reduction Furnace), four STLs (Atomizer, Dehydrator, Dryer, and Magnetic Separator), and three CRLs (Crusher, Classifier and Blender). Table 2 lists the parameters of these three types of loads, i.e., the production rate (Ton/h), energy demand (kWh) and buffer capacity (Ton), where the parameter values are generally taken from [22, 46]. The final product requirement is chosen as 80 Ton, and the maximum amount of electricity $E^{\max}$ that can be drawn from the grid is set at 500 kWh [47]. The DR management simulations are conducted on a rolling basis for each hour, as explained in Section 3, and the formulated MILP problem is solved using the Gurobi solver [48] on the same computer described above. The computation time for working out a single-slot optimized solution is on average 2 s, which fully meets the time requirement for deploying RTP-based DR management in industrial facilities.

4.2. *Simulation Results*

4.2.1. *Performance of the Price Forecasting Approach*

To validate the efficiency of the proposed LSTM RNN, another two classic price forecasting approaches, including autoregressive integrated moving average (ARIMA), and a single hidden layer feed forward neural network (FFNN) are used for comparison and assessed under the preceding calculated indictors (MAE, MAPE, and RMSE). In ARIMA (p, d, q), p is the autoregressive term, q is the moving average window, and d is the degree of differencing (the number of times the data have had past values subtracted). In FFNN, the active function is a sigmoid, and a backward propagation algorithm is used to train the network. When conducting simulations, d is set to 2, p and q are determined from the autocorrelation graph and partial correlation graph of the price data, and the number of hidden nodes in FFNN is set to 30. These parameters are calibrated carefully for a fair comparison.

As illustrated in Table 3, the LSTM RNN outperforms the other two approaches under each statistical indicator. This proves that the proposed method provides more accurate point forecasts, for the reason of LSTM RNN can precisely learn complex nonlinear relations of different price factors, and maintain memory states for prediction based on the information learned. To visualize the prediction results, Fig. 5 shows a comparison of the predictive performance over the testing data set, where the blue line denotes the actual values and other lines denote a series of forecasted quantiles. Intuitively, the prediction results of LSTM RNN are quite well compared with the original time series. It can effectively capture the trends and fluctuations, except for only a few large or sudden changes. In these highly volatile price profiles, the performance of the other methods considered is generally unsatisfactory. Although FFNN captures the general trend of the price time series, the forecasting results are quite spurious, resulting in large error indictors. ARIMA also does not work well in this longer horizon forecasting problem due to the non-stationarity of the price time series.

Summing up the above analyses, the LSTM RNN approach takes its advantages of memorizing long-term historical data and learning more complex nonlinear relationships, leading to the best prediction accuracy. Thus, in the DR decision making process, we use the price forecasting results of the LSTM RNN method.

4.2.2. *Performance of the Demand Response Algorithm*

To demonstrate the performance of the proposed RTP-based DR scheme for the energy management of industrial facilities, a benchmark without DR is designed where fixed flat prices (equal to the average value of dynamic prices) are applied to the objective function (9), that just simply minimize the daily cost by aggregating the cost of each hour. Figs. 6 and 7 show the aggregated energy consumption of all machines without and with

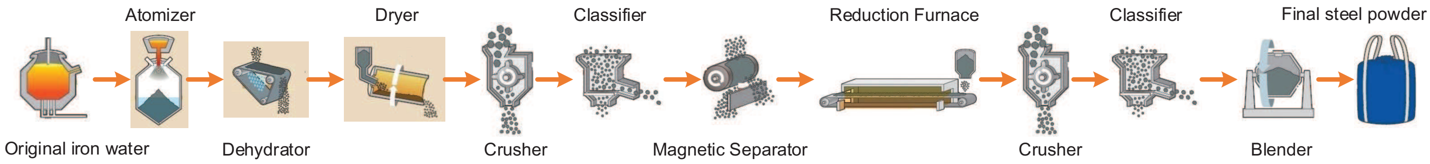

Figure 4: An entire practical steel powder manufacturing process.

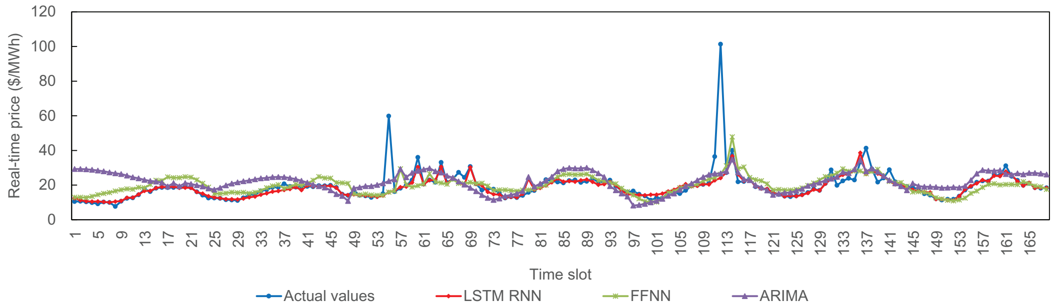

Figure 5: Comparison of the predictive performance over testing data set.

DR on August 31, 2019, respectively. Clearly, the industrial facility has no motivation to reduce or shift its electricity demand when the fixed flat prices are applied, but simply schedules the electricity demand at the beginning to complete the daily production target (referring to Eq. (10)) as early as possible.

In comparison, the electricity consumption is scheduled appropriately when the RTP-based DR scheme in Section 3 is used. It can update the scheduling plan in time based on the actual received price and accurate prediction information, which reduces the effects of uncertain factors on scheduling results. Specifically, the entire electricity demand of STLs and CTLs is scheduled to off-peak slots, i.e., the machines consume more energy at 1-14 h, and reduce their demand at 15-19 h (highest electricity price periods). This is because there is enough storage in each buffer, so the STLs and CTLs stop running at 15-19 h (only NSL consumes energy) to reduce the electricity cost. Due to the capacity limitation of each buffer, the machines cannot stop producing for a long time, and the STLs and CTLs start running again at 20 h to meet the production output requirement. Thus, the overall electricity demand is maintained at quite a low level during peak slots, and only the NSL needs to operate, with the two other types of loads ceased, confirming that the proposed DR algorithm can manage energy consumption properly. It can also be seen that the energy consumption increases slightly during hours 20 and 22, and the reason for this is that the RTP suddenly decreases compared to hours 19 and 21. This small variation in energy consumption further proves the established optimization model is able to respond to instantaneously varying RTPs in an effective way, indicating that the RTP-based DR can play a significant role in peak shaving and valley filling for a power grid.

To gain insights into the manufacturing process under the proposed DR scheme, the storage amount of final steel powder is selected to illustrate the production procedure throughout the whole time horizon. As shown in Fig. 8, more steel powder is produced and stored in low-price periods, as the CRLs

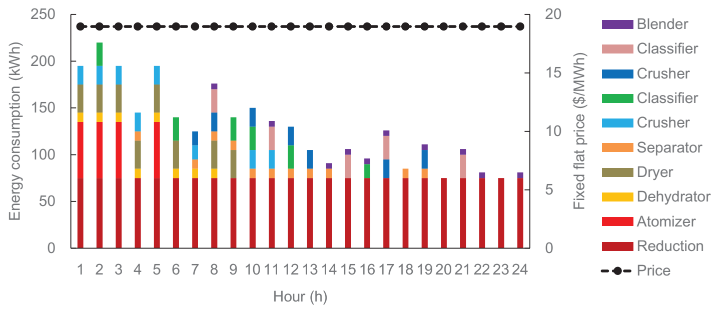

Figure 6: Aggregated energy consumption of all machines without DR.

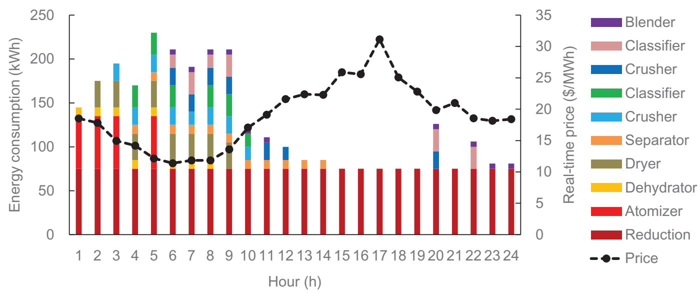

Figure 7: Aggregated energy consumption of all machines with DR.

and STLs are operated at a high energy consumption operating point. Then, it can be seen that the storage amount remains unchanged when the electricity prices are high, because the CRLs and STLs are scheduled to work at a low energy consumption operating point to reduce the electricity cost. After that, the storage amount increases continuously when RTPs are low again. Such a stacking process is correlated with the optimal load scheduling result in Fig. 7, which not only alleviates the stress on the power grid, but also reduces the cost of the industrial facilities.

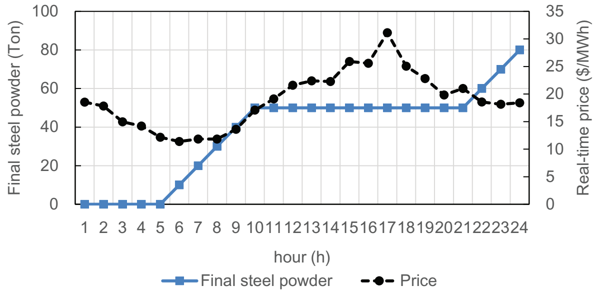

Figure 8: Storage amount of final steel powder.

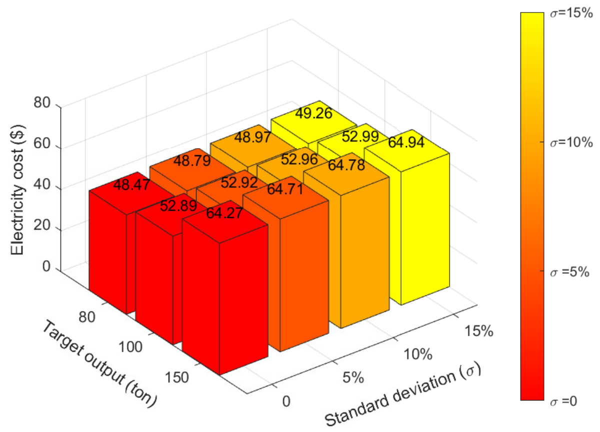

Figure 9: Electricity cost with varying standard deviation.

Table 4: Electricity Cost Without and With DR

Target output	Without DR	With DR			
		(σ= 0)	(σ= 5%)	(σ= 10%)	(σ= 15%)
80	55.91	48.47 (13.31%)	48.79 (12.73%)	48.97 (12.41%)	49.26 (11.89%)
100	58.50	52.89 (9.59%)	52.92 (9.54%)	52.96 (9.47%)	52.99 (9.42%)
150	66.75	64.27 (3.72%)	64.71 (3.06%)	64.78 (2.95%)	64.94 (2.71%)

In the previous analyses, the results are derived based on the assumption that accurate information is available for price forecasting, including historical electricity prices, energy demands and ambient temperature. In practice, mismatches in RTP forecasts are inevitable, and these mismatches may undermine the performance of the schedules obtained by the DR scheme. Therefore, an error sensitivity study is conducted to examine the impact of the mismatches and the robustness of the proposed DR algorithm. In keeping with previous work [49, 50], the prediction errors of RTPs are assumed to follow a normal distribution, with a mean of 0 and standard deviations of 5%, 10%, and 15%, respectively. Then, the future prices used in the simulations are assumed to be the forecasted value plus the prediction error sampled from the normal distribution with different standard deviations. Fig. 9 shows the electricity cost with varying standard deviations under different target production outputs. The first column bar charts represent the expected cost if the forecast is 100% accurate (σ = 0), and the second to fourth column bar charts denote the actual costs considering the forecasting error, where σ= 5%, 10%, 15%, separately. It can be seen that, even with mismatches considered, the actual costs increase slightly with a growing of σ, but they are still very close to the expected cost under different target production settings, demonstrating the good robustness of the proposed RTP-based DR algorithm.

The DR capability is mainly reflected in the response ability to the electricity prices, i.e., whether there is enough time to adjust the working schedule to meet the production target. We define the DR capability as the difference between the electricity cost with and without response to varying electricity prices under different production outputs. Table 4 shows the effects of the production output requirement on DR capability in three scenarios. Scenario one is normal target production output (Ton) in a day (S^{tar}= 80), and scenario two and three have an increased production output of 25% (S^{tar}= 100) and 87.5% (S^{tar}= 150) greater than scenario one. Relative to the case without DR, the daily cost ($) with DR ($\sigma$ = 0 in this situation) is reduced by 13.31%, 9.59%, and 3.72%, respectively. And the reduction in electricity cost with different standard deviation σ is also listed in Table 4. It can be concluded that the RTP-based DR can effectively reduce the electricity cost by shifting energy consumption from peak to off-peak periods, which serves as the core motivation for industrial facilities to participate in the RTP-based DR program. Based on the results, it can also be observed that the greater the production to be completed within a given period, the lower the ability to respond to prices. This is because, with more production to be completed, all machines have to work for a longer time, resulting in higher energy consumption. In particular, when the production output requirement is increased to 150, the system still has a certain response capability under the proposed DR scheme, but this is close to the result without DR.

To evaluate the scalability and flexibility of the proposed RTP-based DR scheme for industrial facilities energy management, we also conduct the simulation from a single day to three different days, wherein the electricity prices are obtained from PJM [44] on the date from August 28 to August 30, 2019. Figs. 10 and 11 show the optimal aggregated energy consumption of all machines under the DR case and the corresponding total electricity cost without and with DR in these three continuous days, respectively. As shown in Fig. 10, similar trend of energy consumption profiles with the previous single day are repeated on each of the three days that verifies the entire electricity demand of all machines is scheduled to off-peak slots to ensure the bill savings, which further enhances the simulation analysis before. Fig. 11 shows the total electricity cost in the case when proposed RTP-based DR scheme is deployed (purple bar), is reduced significantly by 12.34%, compared to the case when no DR is applied (yellow bar), indicating that the proposed DR scheme can handle the industrial energy management well.

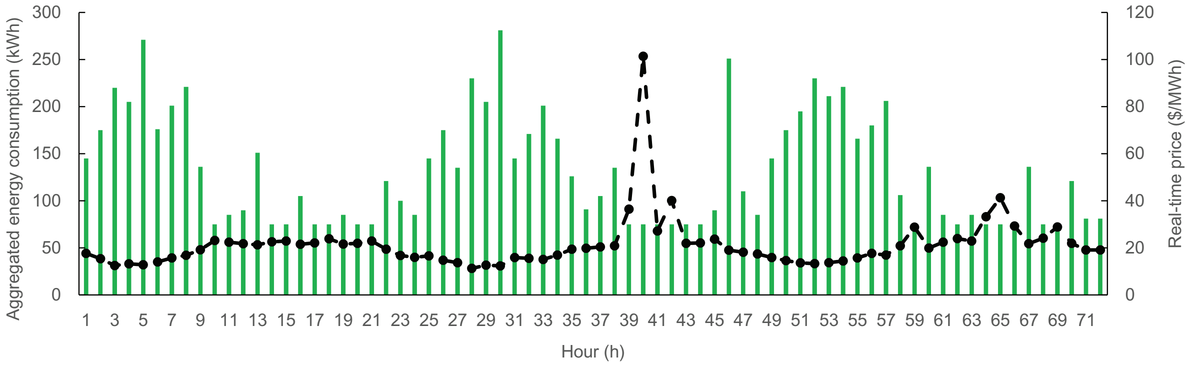

Figure 10: Aggregated energy consumption of all machines with DR from August 28 to August 30, 2019.

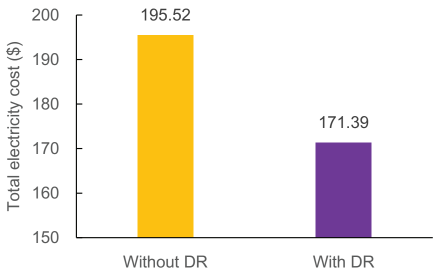

Figure 11: Total cost comparison from August 28 to August 30, 2019.

5. Conclusions and Future Work

Industry energy management is of great significance in reducing energy costs for industrial facilities and improving stability of power grid. This paper proposes an RTP-based DR scheme for energy management of industrial manufacturing processes. The RTP-based DR scheduling horizon not only considers the current time slot, but also takes future slots into account so as to maintain the interdependence of consecutive tasks, and a data-driven approach (realized by LSTM RNN) is adopted to handle future price uncertainties. The decision making procedure with RTP-based DR is formulated as an MILP problem, and the obtained solution yields optimal operating point for each industrial machine. Case studies are carried out for an entire practical steel powder manufacturing process with different designed scenarios. Simulation results demonstrate that the proposed RTP-based DR scheme is able to effectively shift energy consumption from peak to off-peak periods and reduce the electricity cost (i.e., 13.31% decreased), as well as the peak demand of the facility compared to the case without DR, while satisfying all operating constraints. The performance of the presented data-driven RTP forecasting approach is compared to other prediction methods, revealing that LSTM RNN achieves the best forecasting accuracy. Error sensitivity analyses are also conducted to examine the impact of RTP uncertainties, showing that the proposed DR algorithm has good robustness towards prediction errors. Moreover, the DR capability is investigated for a more production (i.e., 150 Ton) to be completed within a given period, the ability of the DR to respond to RTPs will be declined.

In the future, further analyses with the presented RTP-based DR scheme will be conducted, to incorporate the stochastic features of renewable energy resources and energy storage systems, and assess how will impact energy management in industrial facilities. Moreover, deep assessments will be elaborated by investigating how the grid operation status (i.e., external gradient price) affect the performance of the current price forecasting model.

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