Letter

MPC-Based Change Management of Supply Chain Under Disruption Risks: The Case of Battery Industry

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Dear Editor,

The health management of battery supply chain (SC) is vital to battery-related industry. This letter focuses on the study of health management of battery SC under disruptions. First, a discrete-time model of battery SC is developed based on the actual industrial process. Then, a model predictive control-based change management (MPC-CM) strategy is proposed to ensure stable manufacturing of batteries. Moreover, the effects of disruption are also considered in terms of the actual situation. Finally, the validity of the proposed strategy is verified by a case study in Dongsheng Electronics Co., Ltd.

As an important energy storage device, the stable manufacturing of batteries is crucial to battery-related industry, which also plays a key role in battery SC [1]. Due to the integrality and interconnectedness of SC, material flow in SC will be disrupted by unexpected events, such as natural disasters [2] and pandemic outbreak [3]. Different from artificial operational risks, disruptions are usually unpredictable events to SC. In addition, during the past three years, coronavirus disease 2019 (COVID-19) outbreak has always been causing small disturbances or terrible disruptions to SC. Unlike some natural disasters, which can be partially forecast, COVID-19 pandemic is totally unpredictable.

Generally, the spread of COVID-19 disease is difficult to prevent, which largely depends on government's control measures. However, disruptions caused by COVID-19 are not always insurmountable, which have been widely studied in the literature. As an effective SC management strategy, change management of SC during disruptions, which aims to adjust operational policies, is an important manner to improve SC resilience, reduce SC operational cost, enhance corporate competitiveness and improve service levels. Disruption severity-based SC recovery model is built by using mathematical modeling method, and recovery plan is also discussed [4]. Further, SC recovery strategy considering product change under COVID-19 is investigated, and a mixed-integer programming mathematical model is also developed, which can help manufacturer reduce losses effectively [5]. However, although product change strategy can mitigate the effects of disruptions, it still has some limitations. For battery manufacturing, product change incurs extra product design time and costs. To this end, it is suggested that safety stock can help manufacturers reduce stockout risks [6]. It is pointed out that the accurate prediction of customers demands can track customer behaviour during disruptions [7]. As a result, suppliers and manufacturers can arrange procurement and manufacturing in advance.

In this letter, MPC strategy is adopted, which has been successfully applied in the some industries [8]. MPC employs a mathematical model of a controlled system to predict its evolution as a function of actions performed within a specific range [8]. The primary goal of MPC strategy is to calculate the optimal inputs by optimizing a given cost function. MPC-based decision strategy is effectively used for inventory management with uncertain supply and demand, which dramatically reduces the redundant stock and financial costs [9]. Furthermore, MPC policy is also successfully verified for multi-medicine inventory management in a hospital [10]. However, only ordering process is studied, and disruptions are also not considered. As a result, it is interesting to develop an MPC-CM strategy for battery SC that involves ordering, manufacturing and delivery processes under disruptions, which motivates this study.

Motivated by the above discussions, this letter aims to develop an MPC-CM strategy for battery SC subject to disruptions. The main contributions of this letter can be concluded as: 1) Battery SC is described as a discrete-time model that extracted from the actual industrial processes. 2) Ordering, manufacturing and delivery processes are all involved, moreover, an MPC-CM strategy is designed for health management of battery SC under disruption risks.

Problem formulation and SC modeling: As depicted in Fig. 1, the battery SC consists of n suppliers, one manufacturer and clients, which are denoted by S_i, M and C, respectively, $i \in \mathcal{N} = \{1, 2, \dots, n\}$. The arcs in Fig. 1 represent corresponding ordering, manufacturing and delivery processes. Specifically, clients place orders to manufacturer in time period k, manufacturer immediately makes responses without delay, if manufacturer's stock can not satisfy clients, then stockout incurs. The same manipulations are also needed for suppliers and manufacturer. SC disruptions caused by COVID-19 usually appear first on the supply side, which will lead to decrease of suppliers' capacity. Generally, SC disruptions caused by COVID-19 are completely random, which undoubtedly result in unreliable supply. In addition, clients' demands are also unknown to manufacturer in advance. Therefore, it is a challenging task for SC to fulfill all the orders at the least cost with unreliable supply and uncertain demands. The goal of SC is to determine the optimal production planning and inventory replenishment order quantities for suppliers and manufacturer during disruptions. To this end, the objective of this letter is to design an MPC-CM strategy for SC under disruptions such that it can reduce operational costs together with maintaining service levels.

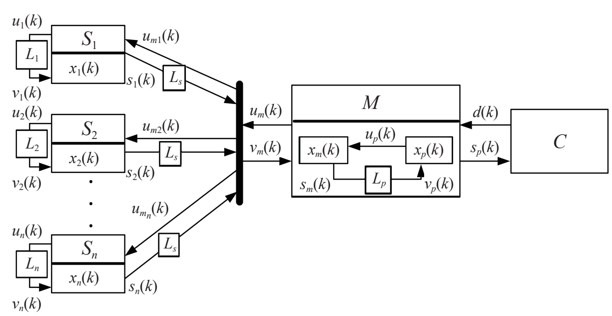

Fig. 1. Ordering, manufacturing and sales processes in battery supply chain.

Depending on the ordering and delivery relationships in Fig. 1, as inventory of each entity varies, the dynamics of studied SC can be described as a discrete-time model

$$x(k+1) = x(k) + v(k+1) - s(k+1) \tag{1}$$

where $x(k) = [x_1(k), \dots, x_n(k), x_m(k), x_p(k)]^T$, $v(k) = [v_1(k), \dots, v_n(k), v_m(k), v_p(k)]^T$, $s(k) = [s_1(k), \dots, s_n(k), s_m(k), s_p(k)]^T$, $x(0) = x_0$, $v(0) = v_0$ and $s(0) = s_0$. $x_i(k)$ and $x_m(k)$ represent the on-hand raw material inventory levels of supplier i and manufacturer, respectively. $v_i(k)$ denotes the raw material quantities that supplier i obtains, $s_i(k)$ is delivery quantities of raw materials from supplier i to manufacturer, $v_m(k)$ denotes quantities of raw materials that manufacturer receives, $s_m(k)$ represents the quantities of raw materials put into production, $x_p(k)$ represents the on-hand finished products inventory of manufacturer, $v_p(k)$ denotes finished products obtained by manufacturer,

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Citation: Y. Yang and C. Peng, "MPC-based change management of supply chain under disruption risks: The case of battery industry," *IEEE/CAA J. Autom. Sinica*, vol. 10, no. 9, pp. 1896–1898, Sept. 2023.

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Digital Object Identifier 10.1109/JAS.2023.123294

$s_p(k)$ stands for delivery quantities of products from manufacturer to clients. In which, k represents time period k.

In addition, it can be deduced that the parameters employed in Fig. 1 satisfy the following relationships: $v_i(k) = u_i(k-L_i)$, $v_m(k) = \sum_{i=1}^{n} s_i(k-L_s)$, $v_p(k) = s_m(k-L_p)$, $u_m(k) = \sum_{i=1}^{n} u_{m_i}(k)$, $u_{m_i}(k) = \lambda_i u_m(k)$, and $\sum_{i=1}^{n} \lambda_i = 1$, $i \in \mathcal{N}$. Then, (1) can be rewritten as follows:

$$\begin{cases} x_i(k+1) = x_i(k) + u_i(k-L_i) - s_i(k) \\ x_m(k+1) = x_m(k) + v_M(k) - s_m(k) \\ x_p(k+1) = x_p(k) + s_m(k-L_p) - s_p(k) \end{cases} \tag{2}$$

where $u_i(k)$ represents raw materials supplier i plans to produce. L_i and L_p are production time for supplier i and manufacturer, respectively. L_s is shipment time from supplier i to manufacturer, $u_{m_i}(k)$ represents the order manufacturer places to supplier i. Moreover, $d(k)$ is the order clients place to manufacturer.

Without loss of generality, the following assumptions are needed:

1) The conversion ratio of raw material to finished product is 1:1. Suppliers are completely substitutable with each other.

2) If disruption occurs, which will lead to the reduction of affected suppliers' capacity. To this end, change control strategy is needed, i.e., emergency procurement from unaffected supplier(s) at the beginning of pandemics.

As known to all, stockout is not rare in SC. If clients' or manufacturer's demands can not be fulfilled, stockout will incur, dynamic equations of backorders can be described as follows:

$$\begin{cases} b_i(k+1) = b_i(k) + u_{m_i}(k+1) - s_i(k+1), \quad i \in \mathcal{N} \\ b_m(k+1) = b_m(k) + u_p(k+1) - s_m(k+1) \\ b_p(k+1) = b_p(k) + d(k+1) - s_p(k+1) \end{cases} \tag{3}$$

where $b_i(k)$ denotes the accumulated stockouts of raw materials in supplier i up to time period k, $b_i(k) \geq 0$, $b_m(k)$ and $b_p(k)$ represent accumulated stockouts of raw materials and finished products in manufacturer utill time period k, respectively, $b_m(k) \geq 0$ and $b_p(k) \geq 0$. More specifically, it can be further deduced that $s_i(k) = \min\{x_i(k-1) + v_i(k), u_{m_i}(k) + b_i(k-1)\}$, $s_m(k) = \min\{x_m(k-1) + v_m(k), u_p(k) + b_m(k-1)\}$ and $s_p(k) = \min\{x_p(k-1) + v_p(k), d(k)+b_p(k-1)\}$, $i \in \mathcal{N}$.

Optimization problem: In this letter, the main objectives of SC are twofold: 1) improve service levels; 2) the operation cost must be lowered. Denote $b(k) = [b_1(k), \ldots, b_n(k), b_m(k), b_p(k)]^T$ and $b(0) = b_0$, therefore, the objective function is defined as follows:

$$\min_{\mathcal{M}} J = \alpha_1 J_1(x(k), k) + \alpha_2 J_2(u(k), k) + \alpha_3 J_3(b(k), k) \tag{4}$$

where $\mathcal{M}$ is a set that can be expressed as $\mathcal{M} = \{x(k), u(k), b(k), k\}$, J_1, J_2 and J_3 denote the terms involved with inventory storage costs, manufacturing costs and stockout costs, respectively. In which, $J_1 = \sum_{i=1}^{N_p} c_x x(k+i)$, $J_2 = \sum_{i=1}^{N_p} c_u u(k+i)$ and $J_3 = \sum_{i=1}^{N_p} c_b b(k+i)$, where $c_x = [c_{x_1}, \ldots, c_{x_n}, c_{x_m}, c_{x_p}]$, $c_u = [c_{u_1}, \ldots, c_{u_n}, c_{u_p}, c_{u_m}]$ and $c_b = [c_{b_1}, \ldots, c_{b_n}, c_{b_m}, c_{b_p}]$ denote unitary storage cost vector, unitary production cost vector and unitary stockout cost vector, respectively. Besides, α_1, α_2 and α_3 are all weighting parameters, manager can adjust weighting parameters to focus on optimizing the corresponding objective(s).

Remark 1: The priority of optimization objectives is as follows: 1) clients' and manufacturer's orders; 2) the stock levels of each entity; 3) production quantities, i.e., $u_i(k)$ and $u_p(k)$. Moreover, manufacturing costs include shipment costs, thus shipment costs are not considered individually.

In addition, some constraints are essential in practical SC such that

$$\begin{aligned} & x_i(k) \in [x_i^{\min}(k), x_i^{\max}(k)], \quad i \in \mathcal{N} \\ & u_p(k) \in [u_p^{\min}(k), \max\{u_p^{\max}(k), x_m(k)\}] \\ & u_i(k) \in [u_i^{\min}(k), u_i^{\max}(k)], \quad u_{m_i}(k) \in [0, x_i(k)], \quad i \in \mathcal{N} \\ & x_m(k) \in [x_m^{\min}(k), x_m^{\max}(k)], \quad x_p(k) \in [x_p^{\min}(k), x_p^{\max}(k)]. \end{aligned} \tag{5}$$

Remark 2: When disruption occurs, the actual minimum and maximum manufacturing capacity of supplier i are forced to reduce up to $u_{a,m_i}^{\min}(k) = \beta_i u_{m_i}^{\min}(k)$ and $u_{a,m_i}^{\max}(k) = \beta_i u_{m_i}^{\max}(k)$, respectively, $\beta_i \in [0, 1]$.

MPC-CM strategy: In this letter, consider system (2) and optimization problem (4). Here, MPC strategy is employed to calculate the optimal control inputs $u(k)$ N_p periods froward based on on-hand inventory and forecasted orders, however, only the first N_u control actions are adopted while the rest are discarded. N_p and N_u are prediction and control horizons, respectively. At each time period, the calculations are repeated by using the latest information.

The optimization problem (4) can be viewed as a mixed-integer programming (MIP) problem. At each time period, manager checks on-hand inventory to identify if on-hand inventory is enough to satisfy the upcoming demands in the next N_p periods, otherwise, an replenishment order must be placed. In order to describe the process more clearly, Algorithm 1 is provided.

Algorithm 1 Order Replenishment Policy

Step 1: At the time period k, measure the inventory level $x(k)$;

Step 2: Forecast the future demands for manufacturer and suppliers according to historical data in the next N_p periods by Algorithm 1 proposed in [11];

Step 3: If on-hand inventory is enough to guarantee the demands for next N_p consecutive periods, there is no need to take any actions, then wait for the next period and go to Step 1;

Step 4: Otherwise, place a replenishment order by solving (4) subject to (5), then wait for the next period and go to Step 1.

Case study: In this part, the simulation test is performed in Dongsheng Electronics Co., Ltd. from 1 July 2021 to 31 August 2021 by using proposed Algorithm 1, which is committed to producing batteries and located in Zhongshan, Guangdong province, China. During the past two decades, Dongsheng has been always adopting order-up-to (OUT) replenishment policy, i.e., if stock of products is below q, then an order is placed to bring stock to an expected level Q. Further, the low bound q and desired level Q are fixed in OUT policy. Moreover, the threshold q is usually set to $L_p\bar{d}$, where $\bar{d}$ is the average consumption of products in the same period last year, and L_p is the production lead time. To reduce the unnecessary costs, the expected inventory level Q is set to $(L_p + 0.2)\bar{d}$.

As depicted in Remark 1, the priority of optimization goals is provided, hence the corresponding coefficients α_1, α_2 and α_3 in (4) are set to 5, 1 and 200, respectively. In the simulation, the number of main suppliers n is set to 2 due to Dongsheng has two main suppliers. In addition, supplier 1 and 2 are located in Yangzhou and Yueyang, respectively. Moreover, according to the practical SC, lead times L_1, L_2, L_s and L_p are all fixed to 1, all the lower bounds in constraints (5) are set as 0, $x_1^{\max}(k) = 8000$, $x_2^{\max}(k) = 7500$, $x_m^{\max}(k) = 5000$, $x_p^{\max}(k) = 5000$, $u_1^{\max}(k) = 4000$, $u_2^{\max}(k) = 3000$ and $u_p^{\max}(k) = 3000$. Besides, $\bar{d} = 2000$, $c_x = [1, 1, 1, 1]$, $c_u = [2, 2, 3]$, $c_b = [0.1, 0.1, 0.1, 0.2]$, $s_0 = b_0 = [0, 0, 0, 0]$, $u_0 = [0, 0, 0]$, $v_0 = [0, 0, 0, 0]$ and $x_0 = [900, 1250, 2235, 2220]$.

During 31 July to 31 August 2021, Yangzhou had been in lockdown due to epidemic outbreak. Therefore, supplier 1 was forced to shut down and $\beta_1 = 0$. Moreover, supplier 2 was also influenced by pandemics, which capacity coefficient β_2 was reduced to 0.6. As a result, Dongsheng endured heavy financial losses due to the shortage of raw materials. At the beginning (27 July 2021) of epidemics, manager should procure raw materials ahead. Therefore, the two scenarios are considered in the simulation: 1) Suppliers and manufacturer produce and procure raw materials ahead in large quantities before lockdown, respectively, N_p and N_u largely depend on the severity of pandemics, which are set to 10 and 6 days before lockdown, respectively. 2) During the lockdown, depending on the forecast of epidemic trends by authorities, supplier 2 and manufacturer produce and procure the right amount of raw materials. Further, N_p and N_u are set to 5 and 1 days, respectively. Different from OUT policy, the MPC optimization problem (4) is solved in each time period, which aims to bring stock levels to an expected level. In addition, the expected stock levels are also dynamically adjusted according to historical demand data.

In order to demonstrate the effectiveness of the proposed MPC-CM strategy, the average stockout (AS), average service level (ASL) and total cost (TC) are introduced as follows, which are key performance indicators and presented in Table 1.

$$ASL = \left(\sum_{k=1}^{62} \frac{s_p(k)}{d(k)}\right)/62$$

$$AS = \left(\sum_{k=1}^{62}\left(\sum_{i=1}^{2} b_i(k)+b_m(k)+b_p(k)\right)\right)/62. \tag{6}$$

Table 1. Comparison of Key Performance Indicators by Applying MPC and OUT Policy

Approach	Average stockout	Average service level	Total cost
OUT	698	95.33%	16 687
MPC	153	99.01%	11 256

Further, the definition of total cost is given as (4) with α_1, α_2 and α_3 being 1.

The real and simulated inventory evolution of suppliers and manufacturer are presented in Fig. 2. As can be seen in Fig. 2, before 27 July, due to the dynamically adjusted mechanism of MPC-CM strategy, lower stock levels of each entity can be obtained with the aid of MPC-CM strategy, which lead to lower storage and manufacturing costs. From 27 July, i.e., at the beginning of the epidemic outbreak, manager needs to develop a contingency at once to face the possible shortage of raw materials. Through MPC-CM policy, manager can force the execution of Step 4 in Algorithm 1, hence the optimal emergency procurement quantities for the next N_p days can be obtained.

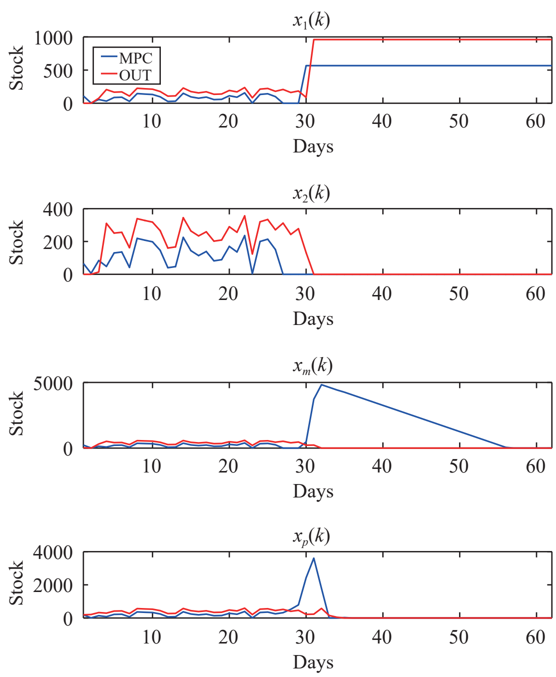

Fig. 2. Real and simulated inventory levels of each entity in SC.

Therefore, from 27 July, $x_m(k)$ and $x_p(k)$ are higher than before due to emergency procurement, i.e., MPC-based change control. In addition, $x_1(k)$ remains unchanged from 31 July due to lockdown policy while $x_2(k)$ keeps a zero inventory because of the reduction of capacity. Further, it can be also observed in Table. 1 that the quantities of average stockout and total costs are dramatically reduced by applying MPC policy, meanwhile, average service level is also slightly improved. Therefore, the advantages of MPC-CM strategy are verified.

Conclusion: In this letter, MPC-CM of battery SC under disruptions involved ordering, manufacturing and delivery processes has been investigated. An MPC-CM strategy has been proposed to schedule ordering, manufacturing and delivery processes. Then, the optimization problem is transformed into a MIP problem. Finally, the health management of batteries can be ensured, and the effectiveness of MPC-CM strategy has been demonstrated by a case study compared with real data obtained by currently implemented strategy in Dongsheng. Further, data-based assisted decision-making system for health management of batteries will also be developed.

Acknowledgments: This work was supported by the National Key Research and Development Program (2020YFB1708200).

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