https://doi.org/10.1016/j.rcim.2021.102161

Augmented Lagrangian coordination for energy-optimal allocation of smart manufacturing services

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Abstract

The rapid development of information and communication technologies has triggered the proposition and implementation of smart manufacturing paradigms. In this regard, efficient allocation of smart manufacturing services (SMSs) can provide a sustainable manner for promoting cleaner production. Currently, centralized optimization methods have been widely used to complete the optimal allocation of SMSs. However, personalized manufacturing tasks usually belong to diverse production domains. The centralized optimization methods could hardly include related production knowledge of all manufacturing tasks in an individual decision model. Consequently, it is difficult to provide satisfactory SMSs for meeting customer's requirements. In addition, energy consumption is rarely considered in the SMS allocation process which is unfavorable for performing sustainable manufacturing. To address these challenges, augmented Lagrangian coordination (ALC), a novel distributed optimization method is proposed to deal with the energy-optimal SMS allocation problem in this paper. The energy-optimal SMS allocation model is constructed and decomposed into several loose-coupled and distributed elements. Two variants of the ALC method are implemented to formulate the proposed problem and obtain final SMS allocation results. A case study is employed to verify the superiority of the proposed method in dealing with energy-optimal SMS allocation problems by comparing with the centralized optimization method at last.

Keywords: smart manufacturing service (SMS), energy consumption, SMS allocation, augmented Lagrangian coordination (ALC)

1 Introduction

Modern industries are undergoing significant changes in their business models to overcome the ever-intensive challenges of market competition, global warming, and product personalization. To fulfill the demand for more sustainable and cleaner production, many service-oriented smart manufacturing paradigms such as Internet of Manufacturing Things [1–4], cloud manufacturing [5,6], and social manufacturing [7,8] have been developed under the support of new generation information and communication technologies, e.g. cloud computing [9], Industrial Internet of Things (IoT) [10,11], big data analytics [12], cyber-physical system (CPS) [13–15], digital twin [16,17], and smart product-service systems [18].

As the crucial element of service-oriented smart manufacturing paradigms, smart manufacturing service (SMS) results from the encapsulation of manufacturing capabilities and resources in the shop-floor. SMS allocation aims to allocate SMSs to execute personalized manufacturing tasks through a process of SMS composition and optimal selection [19]. Efficient SMS allocation can not only avoid idle manufacturing resources but also facilitate full-scale sharing and on-demand-use of manufacturing capabilities, which can provide a sustainable manner for implementing smart manufacturing.

The study on realizing the optimal allocation of SMSs has been done by abundant research work. Three major issues are associated with this area. The first issue is to develop efficient cloud-based management platform for achieving the optimal allocation of SMSs, including the blockchain-based service composition platform [20,21], digital dentistry platform [22], additive manufacturing service platform [23], logistics-aware manufacturing service collaboration platform [24], etc. The second issue mainly focuses on constructing SMS allocation models according to different production requirements and constraints. A lot of researchers studied the quality of service (QoS)-based allocation model [25–27]. Meanwhile, the SMS allocation models subjected to the constraints of sustainability consideration [28], service correlation [29], synergy effect [30], long/short-term utility [31] were also investigated. The third issue is concerned about the optimization algorithms for SMS allocation, such as genetic algorithm [27], grey wolf optimizer [25,32], integer bi-level multi-follower programming method [28], extended flower pollination algorithm [26], ensemble optimization approach [33], and artificial bee colony optimization algorithm [34–36].

Despite significant progress has been achieved by the aforementioned studies, quite a few challenges still exist in performing effective and efficient service allocation in the context of smart manufacturing. Firstly, few studies consider energy consumption in the SMS allocation process [37,38]. Industrial enterprises account for nearly fifty percentages of the world’s energy consumption that intensifies the effects of global warming [39,40]. In order to achieve cleaner production, energy consumption should be taken as a key evaluation criterion for getting optimal SMS allocation results [41]. Secondly, most of the existing research adopted centralized methods/strategies to solve SMS allocation problems. However, personalized manufacturing tasks are always diverse and belong to different production domains or disciplines. Centralized methods/strategies with only one decision model usually have limited expertise of each production domain, and they could hardly consider all manufacturing tasks simultaneously. Hence, it is difficult for them to get satisfactory SMS allocation results to meet customers’ manufacturing requirements. Thirdly, SMSs for different manufacturing tasks may have different service-provision modes. It is very little if anything to include all related parameters of SMSs in a single decision model through centralized methods/strategies. In addition, when a huge number of tasks and SMSs are involved, the complexity of the SMS allocation problem becomes extremely high. Bringing all production expertise and service parameters together in a decision model is often regarded as inefficient and undesired. Therefore, the distributed optimization methods/strategies are needed to accomplish energy-optimal SMS allocation and promote more sustainable and cleaner production.

Recently, a novel distributed optimization method named augmented Lagrangian coordination (ALC) was proposed for complex system design [42,43]. As a decomposition-based method, ALC has shown its potential in tackling various complicated engineering problems such as supply chain configuration [44,45] due to its promising features of offering disciplinary decision autonomy, maintaining flexible coordination structure, and keeping mathematical rigor. Given the aforementioned challenges, ALC is used to solve the energy-optimal SMS allocation problem.

The main goal of this paper is to investigate how can ALC method be applied in solving the energy-optimal SMS allocation problem. The following research questions are of our interest: (1) What is the workflow of energy-optimal SMS allocation, and how to construct its mathematical model? (2) How to formulate the energy-optimal SMS allocation problem according to the ALC application procedure? (3) Will the ALC method be effective and efficient in solving the energy-optimal SMS allocation problem?

The remainder of this paper is organized as follows. The service allocation in smart manufacturing and ALC method are briefly introduced in Section 2. Section 3 depicts the mathematical model of energy-optimal SMS allocation. Section 4 illustrates the ALC formulations for the energy-optimal SMS allocation problem. Section 5 presents a case study for testing the proposed method. Conclusions and future work are summarized in Section 6.

2 Overview of SMS allocation and ALC method

The primary purpose of this section is to describe the workflow of SMS allocation and the basic steps of implementing the ALC method.

2.1 Service allocation in smart manufacturing

Fig. 1 demonstrates the workflow of service allocation in smart manufacturing. Three different kinds of entities are included in this process, i.e. customer, service provider, and cloud-based manufacturing platform. The customer acts as the service demander that has many personalized manufacturing requirements to fulfill. The personalized requirements are represented as manufacturing tasks which are then submitted to the cloud-based manufacturing platform and form a task pool. Meanwhile, traditional manufacturing resources such as machine tools and assembly stations, are enabled to be smart, connected, and autonomous with the information and communication technologies (e.g. inserted IoT sensors), and become smart manufacturing resources (SMRs). The service provider indicates the SMR that has manufacturing capabilities to fulfill specific manufacturing requirements. SMRs with their manufacturing capabilities are encapsulated into SMSs and published on the cloud-based manufacturing platform. A service pool will be formed based on the published SMSs. Then, the service allocation process can be implemented.

Firstly, candidate SMSs for each task are selected according to the information of manufacturing tasks and SMSs. An SMS whose capability information can match the requirements of a task is considered as a candidate SMS. The capability information mainly refers to an SMS's process capability, service quality, availability, etc. For example, a milling machine can be a candidate SMS for a milling task. The second is to identify appropriate objectives to accomplish the optimal allocation of SMSs. Time and cost are the two most common objectives during the SMS allocation process. In order to promote sustainable manufacturing, this study considers energy consumption as an extra evaluation parameter for the SMS allocation. Then, invoke the optimization method/strategy to solve the SMS allocation problem. ALC is selected to perform the SMSs allocation to get more satisfactory results in this paper. After obtaining the optimal SMS allocation results, a service provider can get a piece of manufacturing task to perform, and the customer can get a set of SMSs to fulfill its personalized manufacturing requirements.

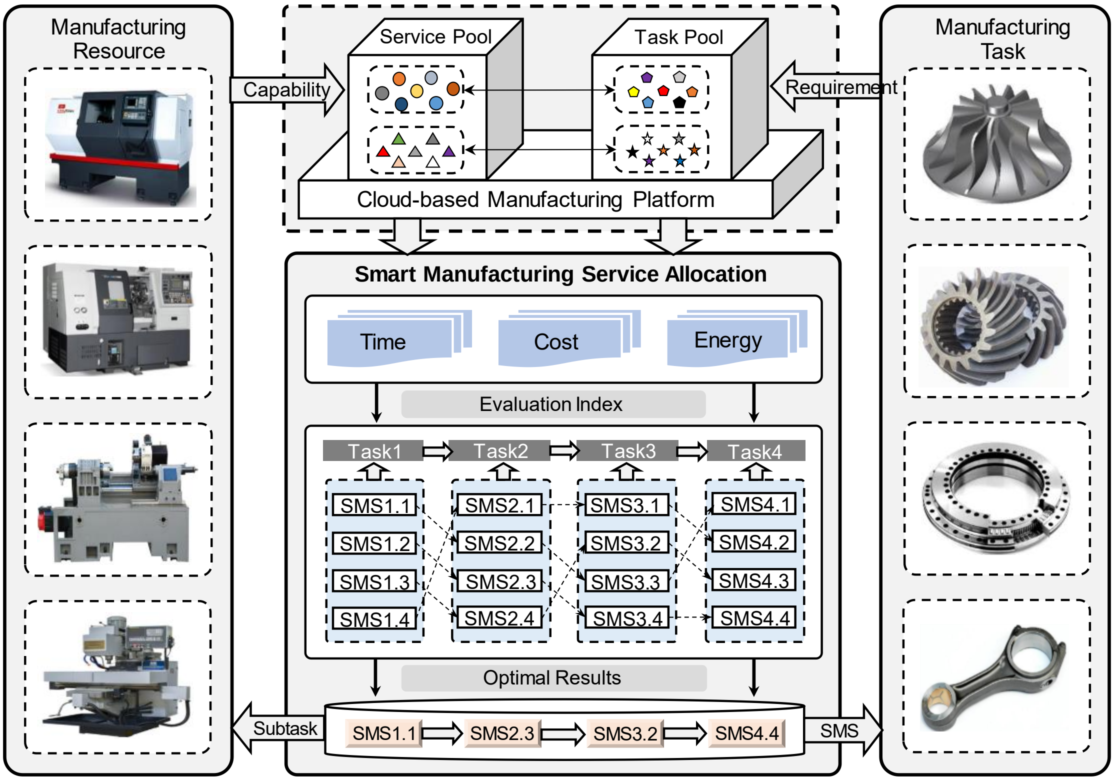

Fig. 1. Workflow of service allocation in smart manufacturing

2.2 ALC method

ALC is a distributed optimization method which is initially used for dealing with multidisciplinary design optimization problems. The major idea of ALC method is to decompose complex system design problem into several elements, and then coordinate the decomposed elements to obtain final optimization results by augmented Lagrangian relaxation and block-coordinate descent (BCD) [43].

The general procedure of adopting the ALC method to solve engineering problems can be described as follows. Firstly, decompose the original problem into a few loose-coupled elements given some specific principles, such as system structure, disciplines. Secondly, identify key links between the decomposed elements. Key links refer to the variables or parameters shared by two or more elements. Thirdly, introduce auxiliary variables of key links to each element, and use the augmented Lagrangian relaxation technology to fully separate coupled elements. Lastly, formulate the separable elements according to different coordination strategies, and get the optimization results. There are two kinds of coordination strategies in the ALC method, i.e. distributed coordination strategy and centralized coordination strategy. Hence, the ALC method is categorized into two variants, distributed ALC and centralized ALC. As shown in Fig. 2, an original problem is decomposed into four elements, i.e. p_1, p_2, p_3, and p_4. Fig. 2(a) shows the distributed ALC solution and Fig. 2(b) shows the centralized ALC solution. Comparing with the distributed solution, an auxiliary element p_0 is introduced to centralized ALC and acts as a master element to coordinate all the decomposed elements. Then, all the decomposed elements can be handled in a parallel manner. In distributed ALC, related elements can be coordinated directly, which provides better convergence efficiency than centralized ALC. The following steps are included in implementing these two coordination strategies.

(1) Set the initial value of variables in all elements and parameters of augmented Lagrangian relaxation.

(2) Use the BCD method to solve each decomposed element with fixed augmented Lagrangian relaxation parameters. In the distributed strategy, the elements are solved iteratively from the higher level to the lower level. For example, p_1 in Fig. 2(a) is solved first, then p_2 in Fig. 2(a) is solved. In the centralized strategy, p_0 in Fig. 2(b) is solved first, then p_1, p_2, p_3, and p_4 in Fig. 2(b) are solved in parallel.

(3) Judge whether the convergence condition is satisfied. If the convergence condition is not satisfied, go to the fourth step; otherwise, terminate the whole procedure and obtain the optimization result.

(4) Update the parameters of augmented Lagrangian relaxation, then return to the second step.

This section is a brief introduction of the ALC method. More detailed information can be referred to [43,46,47].

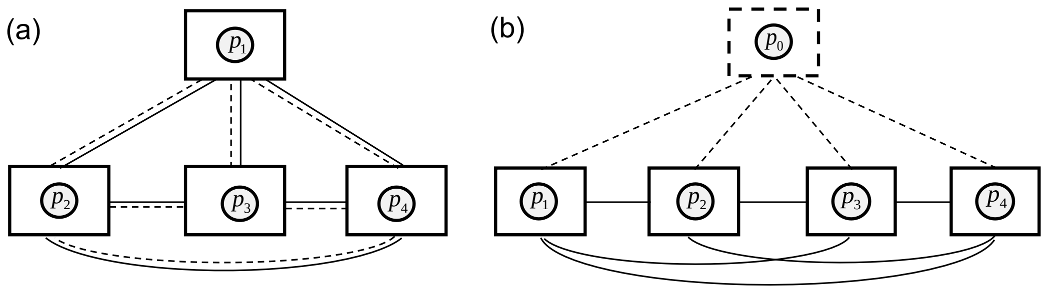

Fig. 2. Two variants of ALC method [43,47]

The reason that ALC is selected to perform the proposed problem can be summarized as two aspects. Regarding the proposed energy-optimal SMS allocation problem, personalized manufacturing tasks always involve multiple production domains or disciplines. Meanwhile, different manufacturing tasks may require diverse service-provision modes. Traditional centralized optimization method with only one decision model could hardly consider both each production domain's expertise and all the service parameters. Hence, a distributed optimization method is needed to perform the energy-optimal SMS allocation problem. In terms of the distributed method, ALC is a decomposition-based method which was proposed for the multidisciplinary design optimization problems. Hence, ALC has the potential to involve multiple production domains or disciplines from personalized manufacturing tasks. Besides, according to the working logic of

ALC method, the original problem can be decomposed into individual elements in a loose-coupled manner. Each decomposed element can have its own decision autonomy. Thus, the diverse service-provision modes can be allowed when using the ALC method to solve the proposed energy-optimal SMS allocation problem. Overall, ALC can be a promising candidate for solving the proposed energy-optimal SMS allocation problem.

3 Mathematical model for energy-optimal SMS allocation

Table 1 Notations

Notations	Description
f	Overall objective of energy-optimal SMS allocation
T	Manufacturing time of completing all tasks
C	Manufacturing cost of completing all tasks
E	Energy consumption of completing all tasks
$T_{\max}$	Maximum manufacturing time of completing all tasks
$C_{\max}$	Maximum manufacturing cost of completing all tasks
$E_{\max}$	Maximum energy consumption of completing all tasks
w_t	Weight coefficient for manufacturing time of completing all tasks
w_c	Weight coefficient for manufacturing cost of completing all tasks
w_e	Weight coefficient for energy consumption of completing all tasks
$O_{i.j}$	jth candidate SMS for ith task
m_i	The number of candidate SMSs for the ith task
$t_{i.j}$	Manufacturing time for $O_{i.j}$ completing the ith task
$c_{i.j}$	Manufacturing cost for $O_{i.j}$ completing the ith task
$e_{i.j}$	Energy consumption for $O_{i.j}$ completing the ith task
$t(i.j,(i-1).k)$	Linking time for $O_{i.j}$ and $O_{(i-1).k}$, $i \ge 2$
$c(i.j,(i-1).k)$	Linking cost for $O_{i.j}$ and $O_{(i-1).k}$, $i \ge 2$
$s_{i.j}$	Selection coefficient for $O_{i.j}$
$\boldsymbol{s}_i$	Vector of selection coefficient for $O_{i.j}$
f_a	Objective function of element p_a
$\boldsymbol{x}^{[a]}$	Vector of auxiliary variables from element p_a
$\boldsymbol{cc}_{a.b}$	consistency constraints for key links between element p_a and element p_b
$\boldsymbol{cc}_{a.b}^{[c]}$	$\boldsymbol{cc}_{a.b}$ associated with p_c element, c=a or b
$\phi_{\boldsymbol{cc}}$	Augmented Lagrangian relaxation function
$\boldsymbol{v}_{a.l}$	lth vector of Lagrangian multiplier parameters of element p_a
$\boldsymbol{w}_{a.l}$	lth vector of Lagrangian weight coefficients of element p_a

In practice, the circumstances of SMS allocation are complex and multiple. For simplicity of understanding, an SMS allocation model shown in Fig. 3 is used to illustrate how the ALC can be applied in solving energy-optimal SMS allocation problems. Notations are listed in Table 1.

The presented SMS allocation model is constructed based on the following assumptions: (1) all tasks in the model follow a serial sequence; (2) candidate SMSs of each task can meet the quality and production capability requirements, and are available for performing related tasks; (3) each candidate SMS can be only selected to perform one task, and each task can be only assigned to one candidate SMS; and (4) time, cost, and energy consumption are considered as the evaluation criteria for getting the optimal SMS allocation results. Note that only the energy consumption which is generated during production processes is considered in this model.

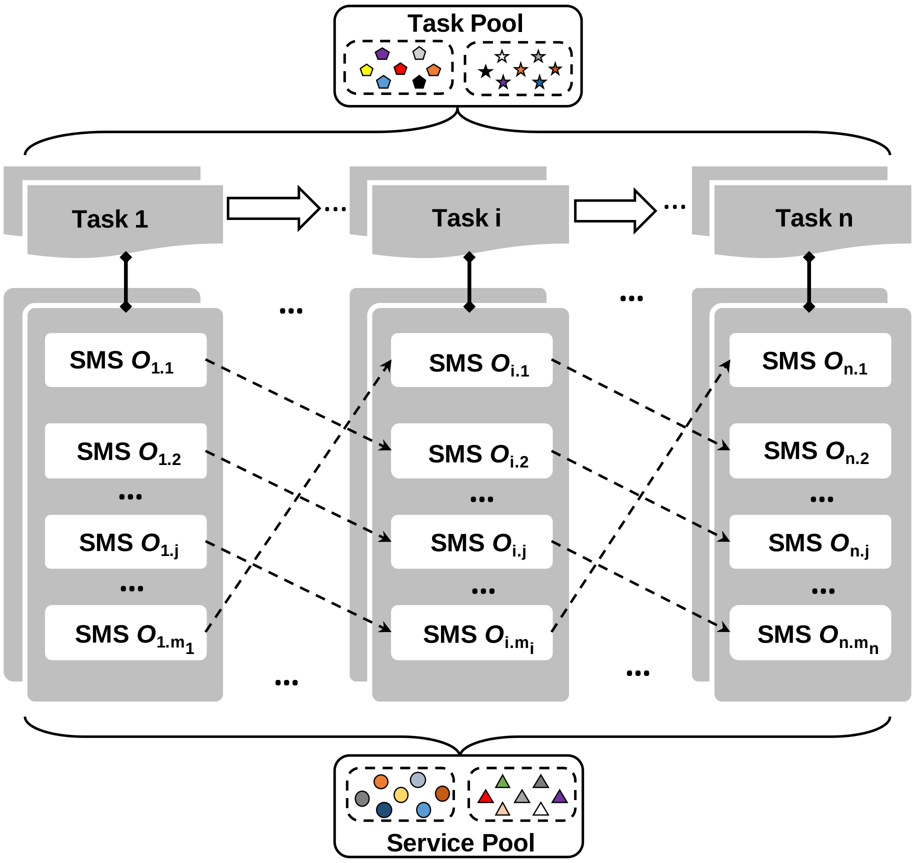

Fig. 3. SMS allocation model

As shown in Fig. 3, n tasks are submitted to the task pool of the cloud-based manufacturing platform. There are m_i candidate SMSs in the service pool to complete task i. The sum of weighted total time, cost and energy consumption is minimized in this model. Then, the mathematical model of this energy-optimal SMS allocation problem can be presented as follows (refer to Table 1 for the description of notations).

Objective function

$$\min f = w_t \frac{T}{T_{\max}} + w_c \frac{C}{C_{\max}} + w_e \frac{E}{E_{\max}} \tag{1}$$

Subject to

$$T=\sum_{i=1}^{n}\sum_{j=1}^{i.m_i} s_{i.j}t_{i.j} + \sum_{i=2}^{n}\sum_{j=1}^{i.m_i}\sum_{k=1}^{(i-1).m_{i-1}} s_{i.j}s_{(i-1).k}t(i.j,(i-1).k) \tag{2}$$

$$C=\sum_{i=1}^{n}\sum_{j=1}^{i.m_i} s_{i.j}c_{i.j} + \sum_{i=2}^{n}\sum_{j=1}^{i.m_i}\sum_{k=1}^{(i-1).m_{i-1}} s_{i.j}s_{(i-1).k}c(i.j,(i-1).k) \tag{3}$$

$$E=\sum_{i=1}^{n}\sum_{j=1}^{i.m_i} s_{i.j}e_{i.j} \tag{4}$$

$$s_{i.j} = \begin{cases} 1, \text{ If } O_{i,j} \text{ is selected} \\ 0, \text{ Otherwise} \end{cases} \tag{5}$$

$$\sum_{j=1}^{i.m_i} s_{i.j} = 1 \tag{6}$$

Eq. (1) represents the objective function. It consists of three parts, i.e. weighted T, C cost, and E of completing all tasks. $T_{\max}$, $C_{\max}$, and $E_{\max}$ are used to nondimensionalize each part. Eqs. (2)-(4) are employed to calculate T, C cost, and E of completing all tasks. The total manufacturing time T is composed of the manufacturing time of each task and the linking time between two related SMSs. The linking time mainly refers to the logistics time and storage time. Similarly, the total manufacturing cost C consists of the manufacturing cost of each task and the linking cost between two related SMSs. The linking cost mainly refers to the logistics cost and storage cost. As the aforementioned assumption, only the energy consumption of manufacturing phases is calculated in the formulation. Eqs. (5)-(6) ensure that only one SMS will be selected to complete task i.

In order to better illustrate the following ALC formulations, eqs. (2)-(4) are inserted into eq. (1). Then, the mathematical model of energy-optimal SMS allocation can be presented as follows.

Objective function

$$\begin{aligned} \min\ f = {} & w_t \frac{\sum_{i=1}^{n}\sum_{j=1}^{i.m_i} s_{i.j}t_{i.j} + \sum_{i=2}^{n}\sum_{j=1}^{i.m_i}\sum_{k=1}^{(i-1).m_{i-1}} s_{i.j}s_{(i-1).k}t(i.j,(i-1).k)}{T_{\max}} \\ & + w_c \frac{\sum_{i=1}^{n}\sum_{j=1}^{i.m_i} s_{i.j}c_{i.j} + \sum_{i=2}^{n}\sum_{j=1}^{i.m_i}\sum_{k=1}^{(i-1).m_{i-1}} s_{i.j}s_{(i-1).k}c(i.j,(i-1).k)}{C_{\max}} + w_e \frac{\sum_{i=1}^{n}\sum_{j=1}^{i.m_i} s_{i.j}e_{i.j}}{E_{\max}} \end{aligned} \tag{7}$$

Subject to

$$s_{i.j} = \begin{cases} 1, \text{ If } O_{i,j} \text{ is selected} \\ 0, \text{ Otherwise} \end{cases} \tag{8}$$

$$\sum_{j=1}^{i.m_i} s_{i.j} = 1 \tag{9}$$

4 ALC formulations for energy-optimal optimal allocation of SMSs

4.1 Decomposition of the original problem

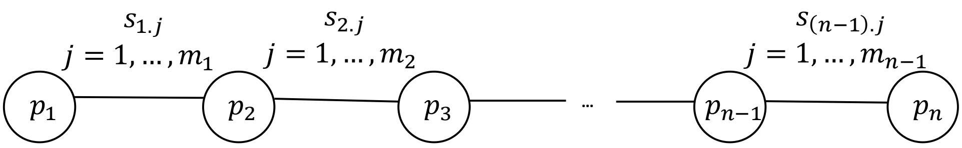

Fig. 4. Decomposition model of original problem

According to the procedure of adopting ALC to solve engineering problems, the first is to decompose original energy-optimal SMS allocation problem into several elements. Since different tasks may belong to different production domains or disciplines, the required SMS provision mode for each task may be different. Hence, in this study, the production domain of each task can be considered as the rule to decompose the original energy-optimal SMS allocation problem. Assume that each task in Fig. 3 belongs to a different production domain. Then, the decomposition of the original problem can be presented as Fig. 4 which consists of n elements, i.e. p_1, p_2, …, p_n.

Based on the decomposition model, the mathematical model presented by eqs. (7)-(9) can be rewritten as follows.

Objective function

$$\begin{aligned} \min f = & \sum_{j=1}^{1.m_1} s_{1.j}\left(w_t \frac{t_{1.j}}{T_{\max}} + w_c \frac{c_{1.j}}{C_{\max}} + w_e \frac{e_{1.j}}{E_{\max}}\right) + \sum_{i=2}^{n}\left(\sum_{j=1}^{m_i} s_{i.j}\left(w_t \frac{t_{i.j}}{T_{\max}} + w_c \frac{c_{i.j}}{C_{\max}} + w_e \frac{e_{i.j}}{E_{\max}}\right) \right. \\ & \left. + \sum_{j=1}^{m_i}\sum_{k=1}^{m_{i-1}} s_{i.j} s_{(i-1).k}\left(w_t \frac{t(i.j,(i-1).k)}{T_{\max}} + w_c \frac{c(i.j,(i-1).k)}{C_{\max}}\right)\right) \end{aligned} \tag{10}$$

Subject to

$$s_{i.j} = \begin{cases} 1, \text{ If } O_{i.j} \text{ is selected} \\ 0, \text{ Otherwise} \end{cases} \tag{11}$$

$$\sum_{j=1}^{i.m_i} s_{i.j} = 1 \tag{12}$$

As it can be seen from Fig. 4 and the rewritten mathematical model, element p_i and $p_{i\text{-}1}$ ($i \geq 2$) are linked by $s_{(i-1).1}, \ldots, s_{(i-1).j}, \ldots, s_{(i-1).m_{i-1}}$. Hence, the key links between element p_i and $p_{i\text{-}1}$ ($i \geq 2$) are identified as $s_{(i-1).1}, \ldots, s_{(i-1).j}, \ldots, s_{(i-1).m_{i-1}}$. Define $\boldsymbol{s}_i = [s_{i.1}, s_{i.2}, \ldots, s_{i.m_i}]^T$. The key links in this model can be represented as $\boldsymbol{s}_1, \ldots, \boldsymbol{s}_{i\text{-}1}, \ldots, \boldsymbol{s}_{n-1}$.

4.2 Distributed ALC formulations for energy-optimal SMS allocation

This primary goal of this part is to illustrate the distributed ALC formulations for energy-optimal SMS allocation. Based on the identified key links in the decomposition model, related auxiliary variables and consistency constraints are introduced to each decomposed element and listed in Table 2.

Table 2 Auxiliary variables and consistency constraints for distributed ALC

Decomposed element	Link variable	Auxiliary variable	Consistency constraints
p_1	$\boldsymbol{s}_1$	$\boldsymbol{s}_1^{[1]}$	$\boldsymbol{cc}_{1.2}=\boldsymbol{s}_1^{[1]}-\boldsymbol{s}_1^{[2]}$
$p_i \quad (2 \le i \le n\text{-}1)$	$\boldsymbol{s}_{i-1}$, $\boldsymbol{s}_i$	$\boldsymbol{s}_{i-1}^{[i]}$, $\boldsymbol{s}_i^{[i]}$	$\boldsymbol{cc}_{(i-1).i}=\boldsymbol{s}_{i-1}^{[i-1]}-\boldsymbol{s}_{i-1}^{[i]}$, $\boldsymbol{cc}_{i.(i+1)}=\boldsymbol{s}_i^{[i]}-\boldsymbol{s}_i^{[i+1]}$
p_n	$\boldsymbol{s}_{n-1}$	$\boldsymbol{s}_{n-1}^{[n]}$	$\boldsymbol{cc}_{(n-1).n}=\boldsymbol{s}_{n-1}^{[n-1]}-\boldsymbol{s}_{n-1}^{[n]}$

Then, the formulation of each element is presented as follows.

- Formulation of p_1

Objective function

$$\min\ f_1=\sum_{j=1}^{1.m_1}\boldsymbol{s}_1^{[1]}(j)(w_t\frac{t_{1.j}}{T_{\max}}+w_c\frac{c_{1.j}}{C_{\max}}+w_e\frac{e_{1.j}}{E_{\max}})+\phi_{\boldsymbol{cc}}(\boldsymbol{s}_1^{[1]}-\boldsymbol{s}_1^{[2]}) \tag{13}$$

Subject to

$$\phi_{\boldsymbol{cc}}(\boldsymbol{s}_1^{[1]}-\boldsymbol{s}_1^{[2]})=\boldsymbol{v}_{1.1}^T(\boldsymbol{s}_1^{[1]}-\boldsymbol{s}_1^{[2]})+\|\boldsymbol{w}_{1.1}\circ(\boldsymbol{s}_1^{[1]}-\boldsymbol{s}_1^{[2]})\|_2^2 \tag{14}$$

$$\boldsymbol{s}_1^{[1]}(j)=\begin{cases}1, \text{ If } O_{1.j} \text{ is selected}\\ 0, \text{ Otherwise}\end{cases} \tag{15}$$

$$\sum_{j=1}^{1.m_1}\boldsymbol{s}_1^{[1]}(j)=1 \tag{16}$$

The formulation of p_1 is with respect to $\boldsymbol{s}_1^{[1]}$, and solved with fixed $\boldsymbol{s}_1^{[2]}$. The objective function of p_1 includes two items. The first item is the sum of weighted manufacturing time, cost, and energy consumption for completing task 1. The second item is augmented Lagrangian relaxation for the consistency constraints which are related to element p_1. Eq. (14) represents the augmented Lagrangian relaxation for $\boldsymbol{cc}_{1.2}$. Eqs. (15)-(16) ensure that only one SMS will be selected to complete task 1.

- Formulation of $p_i \quad (2 \le i \le n\text{-}1)$

Objective function

$$\begin{aligned}\min\ f_i=&\sum_{j=1}^{m_i}\boldsymbol{s}_i^{[i]}(j)(w_t\frac{t_{i.j}}{T_{\max}}+w_c\frac{c_{i.j}}{C_{\max}}+w_e\frac{e_{i.j}}{E_{\max}})\\&+\sum_{j=1}^{m_i}\sum_{k=1}^{m_{i-1}}\boldsymbol{s}_i^{[i]}(j)\boldsymbol{s}_{i-1}^{[i]}(k)(w_t\frac{t(i.j,(i-1).k)}{T_{\max}}+w_c\frac{c(i.j,(i-1).k)}{C_{\max}})\\&+\phi_{\boldsymbol{cc}}(\boldsymbol{s}_{i-1}^{[i-1]}-\boldsymbol{s}_{i-1}^{[i]})+\phi_{\boldsymbol{cc}}(\boldsymbol{s}_i^{[i]}-\boldsymbol{s}_i^{[i+1]})\end{aligned} \tag{17}$$

Subject to

$$\phi_{\boldsymbol{cc}}(\boldsymbol{s}_{i-1}^{[i\text{-}1]}-\boldsymbol{s}_{i-1}^{[i]})=\boldsymbol{v}_{i.1}^{T}(\boldsymbol{s}_{i-1}^{[i\text{-}1]}-\boldsymbol{s}_{i-1}^{[i]})+\|\boldsymbol{w}_{i.1}\circ(\boldsymbol{s}_{i-1}^{[i\text{-}1]}-\boldsymbol{s}_{i-1}^{[i]})\|_{2}^{2} \tag{18}$$

$$\phi_{\boldsymbol{cc}}(\boldsymbol{s}_{i}^{[i]}-\boldsymbol{s}_{i}^{[i+1]})=\boldsymbol{v}_{i.2}^{T}(\boldsymbol{s}_{i}^{[i]}-\boldsymbol{s}_{i}^{[i+1]})+\|\boldsymbol{w}_{i.2}\circ(\boldsymbol{s}_{i}^{[i]}-\boldsymbol{s}_{i}^{[i+1]})\|_{2}^{2} \tag{19}$$

$$\boldsymbol{s}_{i-1}^{[i]}(k)=\begin{cases}1, \text{ If } O_{(i-1).k} \text{ is selected}\\ 0, \text{ Otherwise}\end{cases} \tag{20}$$

$$\sum_{k=1}^{(i\text{-}1).m_{i-1}}\boldsymbol{s}_{i-1}^{[i]}(k)=1 \tag{21}$$

$$\boldsymbol{s}_{i}^{[i]}(j)=\begin{cases}1, \text{ If } O_{i.j} \text{ is selected}\\ 0, \text{ Otherwise}\end{cases} \tag{22}$$

$$\sum_{j=1}^{i.m_i}\boldsymbol{s}_{i}^{[i]}(j)=1 \tag{23}$$

The formulation of p_i is with respect to $\boldsymbol{s}_{i-1}^{[i]}$ and $\boldsymbol{s}_{i}^{[i]}$, and solved with fixed $\boldsymbol{s}_{i-1}^{[i\text{-}1]}$ and $\boldsymbol{s}_{i}^{[i+1]}$. The objective function of p_i consists of three parts. The first part consists of the weighted manufacturing time, cost, and energy consumption for completing task *i*. The second part is the sum of weighted linking cost time and cost between element p_i and p_{i-1}. The third part is augmented Lagrangian relaxation for the consistency constraints which are related to element p_i. Eqs. (18)-(19) represent the augmented Lagrangian relaxation for $\boldsymbol{cc}_{(i-1).i}$ and $\boldsymbol{cc}_{i.(i+1)}$. Eqs. (20)-(21) ensure that only one SMS will be selected to complete task *i*-1. Eqs. (22)-(23) ensure that only one SMS will be selected to complete task *i*.

- Formulation of p_n

Objective function

$$\begin{aligned}\min\ f_n=&\sum_{j=1}^{m_n}\boldsymbol{s}_n(j)(w_t\frac{t_{n.j}}{T_{\max}}+w_c\frac{c_{n.j}}{C_{\max}}+w_e\frac{e_{n.j}}{E_{\max}})\\&+\sum_{j=1}^{m_n}\sum_{k=1}^{m_{i-1}}\boldsymbol{s}_n(j)(j)\boldsymbol{s}_{n-1}^{[n]}(k)(w_t\frac{t(n.j,(n-1).k)}{T_{\max}}+w_c\frac{c(n.j,(n-1).k)}{C_{\max}})+\phi_{\boldsymbol{cc}}(\boldsymbol{s}_{n-1}^{[n-1]}-\boldsymbol{s}_{n-1}^{[n]})\end{aligned} \tag{24}$$

Subject to

$$\phi_{\boldsymbol{cc}}(\boldsymbol{s}_{n-1}^{[n\text{-}1]}-\boldsymbol{s}_{n-1}^{[n]})=\boldsymbol{v}_{n.1}^{T}(\boldsymbol{s}_{n-1}^{[n\text{-}1]}-\boldsymbol{s}_{n-1}^{[n]})+\|\boldsymbol{w}_{n.1}\circ(\boldsymbol{s}_{n-1}^{[n\text{-}1]}-\boldsymbol{s}_{n-1}^{[n]})\|_{2}^{2} \tag{25}$$

$$\boldsymbol{s}_{n-1}^{[n]}(k)=\begin{cases}1, \text{ If } O_{(n-1).k} \text{ is selected}\\ 0, \text{ Otherwise}\end{cases} \tag{26}$$

$$\sum_{k=1}^{(n\text{-}1).m_{n-1}} \boldsymbol{s}_{n-1}^{[n]}(k) = 1 \tag{27}$$

$$\boldsymbol{s}_n(j) = \begin{cases} 1, \text{ If } O_{n.j} \text{ is selected} \\ 0, \text{ Otherwise} \end{cases} \tag{28}$$

$$\sum_{j=1}^{n.m_n} \boldsymbol{s}_n(j) = 1 \tag{29}$$

The formulation of p_n is with respect to $\boldsymbol{s}_{n-1}^{[n]}$, and solved with fixed $\boldsymbol{s}_{n-1}^{[n-1]}$. The objective function of p_n consists of three parts. The first part consists of the weighted manufacturing time, cost, and energy consumption for completing task *n*. The second part is the sum of weighted linking time and cost between element p_n and p_{n-1}. The third part is augmented Lagrangian relaxation for the consistency constraints which are related to element p_n. Eq. (25) represent the augmented Lagrangian relaxation for $\boldsymbol{cc}_{(n-1).n}$. Eqs. (26)-(27) ensure that only one SMS will be selected to complete task *n*-1. Eqs. (28)-(29) ensure that only one SMS will be selected to complete task *n*.

4.3 Centralized ALC formulations for energy-optimal SMS allocation

The primary goal of this section is to illustrate the centralized ALC formulations for energy-optimal SMS allocation. An auxiliary element p_0 is introduced to enable parallel computation of elements p_1, p_2,…, p_n. The decomposition model of the original problem is presented in Fig. 5. In this circumstance, p_1, p_2,…, p_n are fully separable, and p_0 acts as a coordinator to coordinate them by adjusting the shared key links and auxiliary variables.

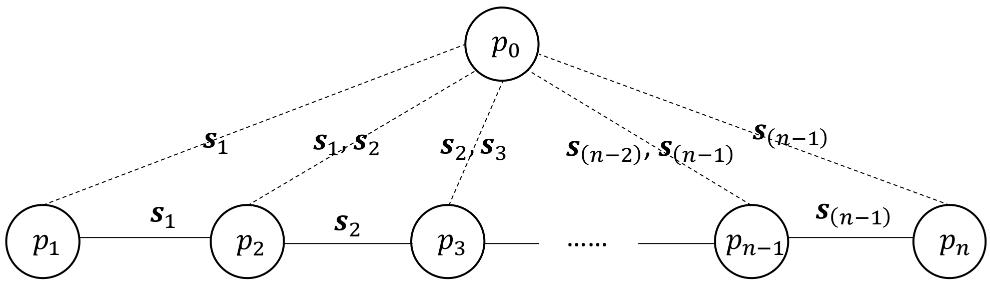

Fig. 5. Decomposition model of original problem and related key links

Based on the identified key links in the decomposition model, related auxiliary variables and consistency constraints are introduced to each element and listed in Table 3.

Table 3 Auxiliary variables and consistency constraints for centralized ALC

Decomposed element	Link variable	Auxiliary variable	Consistency constraints
p_1	$\boldsymbol{s}_1$	$\boldsymbol{s}_1^{[1]}$	$\boldsymbol{cc}_{1.2}^{[1]} = \boldsymbol{s}_1 - \boldsymbol{s}_1^{[1]}$
p_i $(2 \le i \le n\text{-}1)$	$\boldsymbol{s}_{i-1}$, $\boldsymbol{s}_i$	$\boldsymbol{s}_{i-1}^{[i]}, \boldsymbol{s}_i^{[i]}$	$\boldsymbol{cc}_{(i-1).i}^{[i]} = \boldsymbol{s}_{i-1} - \boldsymbol{s}_{i-1}^{[i]}$, $\boldsymbol{cc}_{i.(i+1)}^{[i]} = \boldsymbol{s}_i - \boldsymbol{s}_i^{[i]}$
p_n	$\boldsymbol{s}_{n-1}$	$\boldsymbol{s}_{n-1}^{[n]}$	$\boldsymbol{cc}_{(n-1).n}^{[n]} = \boldsymbol{s}_{n-1} - \boldsymbol{s}_{n-1}^{[n]}$
p_0	$\boldsymbol{s}_i\,(1 \le i \le n\text{-}1)$	$\boldsymbol{s}_i^{[i]}$, $\boldsymbol{s}_i^{[i+1]}$ $(1 \le i \le n\text{-}1)$	$\boldsymbol{cc}_{1.2}^{[1]} = \boldsymbol{s}_1 - \boldsymbol{s}_1^{[1]}$, $\boldsymbol{cc}_{(i-1).i}^{[i]} = \boldsymbol{s}_{i-1} - \boldsymbol{s}_{i-1}^{[i]}$, $\boldsymbol{cc}_{i.(i+1)}^{[i]} = \boldsymbol{s}_i - \boldsymbol{s}_i^{[i]}$, $\boldsymbol{cc}_{(n-1).n}^{[n]} = \boldsymbol{s}_{n-1} - \boldsymbol{s}_{n-1}^{[n]}$

Then, each decomposed element can be formulated as follows.

- Formulations of p_1

Objective function

$$\min\ f_1 = \sum_{j=1}^{1.m_1} \boldsymbol{s}_1^{[1]}(j)(w_t \frac{t_{1.j}}{T_{\max}} + w_c \frac{c_{1.j}}{C_{\max}} + w_e \frac{e_{1.j}}{E_{\max}}) + \phi_{\boldsymbol{cc}}(\boldsymbol{s}_1 - \boldsymbol{s}_1^{[1]}) \tag{30}$$

Subject to

$$\phi_{\boldsymbol{cc}}(\boldsymbol{s}_1 - \boldsymbol{s}_1^{[1]}) = \boldsymbol{v}_{1.1}^T(\boldsymbol{s}_1 - \boldsymbol{s}_1^{[1]}) + \| \boldsymbol{w}_{1.1} \circ (\boldsymbol{s}_1 - \boldsymbol{s}_1^{[1]}) \|_2^2 \tag{31}$$

$$\boldsymbol{s}_1^{[1]}(j) = \begin{cases} 1, \text{ If } O_{i.j} \text{ is selected} \\ 0, \text{ Otherwise} \end{cases} \tag{32}$$

$$\sum_{j=1}^{1.m_1} \boldsymbol{s}_1^{[1]}(j) = 1 \tag{33}$$

The formulation of p_1 is with respect to $\boldsymbol{s}_1^{[1]}$, and solved with fixed $\boldsymbol{s}_1$. The objective function and constraints have the same implications as the formulation of p_1 described in the distributed ALC method.

- Formulations of p_i $(2 \le i \le n\text{-}1)$

Objective function

$$\begin{aligned} \min\ f_i = & \sum_{j=1}^{m_i} \boldsymbol{s}_i^{[i]}(j)(w_t \frac{t_{i.j}}{T_{\max}} + w_c \frac{c_{i.j}}{C_{\max}} + w_e \frac{e_{i.j}}{E_{\max}}) \\ & + \sum_{j=1}^{m_i} \sum_{k=1}^{m_{i-1}} \boldsymbol{s}_i^{[i]}(j) \boldsymbol{s}_{i-1}^{[i]}(k)(w_t \frac{t(i.j,(i-1).k)}{T_{\max}} + w_c \frac{c(i.j,(i-1).k)}{C_{\max}}) \\ & + \phi_{\boldsymbol{cc}}(\boldsymbol{s}_{i-1} - \boldsymbol{s}_{i-1}^{[i]}) + \phi_{\boldsymbol{cc}}(\boldsymbol{s}_i - \boldsymbol{s}_i^{[i]}) \end{aligned} \tag{34}$$

Subject to

$$\phi_{cc}(\boldsymbol{s}_{i-1}-\boldsymbol{s}_{i-1}^{[i]})=\boldsymbol{v}_{i.1}^{T}(\boldsymbol{s}_{i-1}-\boldsymbol{s}_{i-1}^{[i]})+\|\boldsymbol{w}_{i.1}\circ(\boldsymbol{s}_{i-1}-\boldsymbol{s}_{i-1}^{[i]})\|_2^2 \tag{35}$$

$$\phi_{cc}(\boldsymbol{s}_{i}-\boldsymbol{s}_{i}^{[i]})=\boldsymbol{v}_{i.2}^{T}(\boldsymbol{s}_{i}-\boldsymbol{s}_{i}^{[i]})+\|\boldsymbol{w}_{i.2}\circ(\boldsymbol{s}_{i}-\boldsymbol{s}_{i}^{[i]})\|_2^2 \tag{36}$$

$$\boldsymbol{s}_{i-1}^{[i]}(k)=\begin{cases}1, \text{ If } O_{(i-1).k} \text{ is selected}\\ 0, \text{ Otherwise}\end{cases} \tag{37}$$

$$\sum_{k=1}^{(i\text{-}1).m_{i-1}} \boldsymbol{s}_{i-1}^{[i]}(k)=1 \tag{38}$$

$$\boldsymbol{s}_{i}^{[i]}(j)=\begin{cases}1, \text{ If } O_{i.j} \text{ is selected}\\ 0, \text{ Otherwise}\end{cases} \tag{39}$$

$$\sum_{j=1}^{i.m_i} \boldsymbol{s}_{i}^{[i]}(j)=1 \tag{40}$$

The formulation of p_i is with respect to $\boldsymbol{s}_{i-1}^{[i]}$ and $\boldsymbol{s}_{i}^{[i]}$, and solved with fixed $\boldsymbol{s}_{i-1}$ and $\boldsymbol{s}_{i}$. The objective function and constraints have the same implications as the formulation of p_i described in the distributed ALC method.

- Formulations of p_n

Objective function

$$\begin{aligned}&\min\ f_n=\sum_{j=1}^{m_n}\boldsymbol{s}_n(j)\left(w_t\frac{t_{n.j}}{T_{\max}}+w_c\frac{c_{n.j}}{C_{\max}}+w_e\frac{e_{n.j}}{E_{\max}}\right)\\ &+\sum_{j=1}^{m_n}\sum_{k=1}^{m_{i-1}}\boldsymbol{s}_n(j)(j)\boldsymbol{s}_{n-1}^{[n]}(k)\left(w_t\frac{t(n.j,(n-1).k)}{T_{\max}}+w_c\frac{c(n.j,(n-1).k)}{C_{\max}}\right)+\phi_{cc}(\boldsymbol{s}_{n-1}-\boldsymbol{s}_{n-1}^{[n]})\end{aligned} \tag{41}$$

Subject to

$$\phi_{cc}(\boldsymbol{s}_{n-1}-\boldsymbol{s}_{n-1}^{[n]})=\boldsymbol{v}_{n.1}^{T}(\boldsymbol{s}_{n-1}-\boldsymbol{s}_{n-1}^{[n]})+\|\boldsymbol{w}_{n.1}\circ(\boldsymbol{s}_{n-1}-\boldsymbol{s}_{n-1}^{[n]})\|_2^2 \tag{42}$$

$$\boldsymbol{s}_{n-1}^{[n]}(k)=\begin{cases}1, \text{ If } O_{(n-1).k} \text{ is selected}\\ 0, \text{ Otherwise}\end{cases} \tag{43}$$

$$\sum_{k=1}^{(n\text{-}1).m_{n-1}} \boldsymbol{s}_{n-1}^{[n]}(k)=1 \tag{44}$$

$$\boldsymbol{s}_{n}(j)=\begin{cases}1, \text{ If } O_{n.j} \text{ is selected}\\ 0, \text{ Otherwise}\end{cases} \tag{45}$$

$$\sum_{j=1}^{n.m_n} \boldsymbol{s}_{n}(j)=1 \tag{46}$$

The formulation of p_n is with respect to $\boldsymbol{s}_{n-1}^{[n]}$, and solved with fixed $\boldsymbol{s}_{n-1}$. The objective function and constraints have the same implications as the formulation of p_n described in the distributed ALC method.

- Formulations of p_0

Objective function

$$\min\ f_0 = \phi_{cc}(\boldsymbol{s}_1 - \boldsymbol{s}_1^{[1]}) + \sum_{i=2}^{n-1}(\phi_{cc}(\boldsymbol{s}_{i-1} - \boldsymbol{s}_{i-1}^{[i]}) + \phi_{cc}(\boldsymbol{s}_i - \boldsymbol{s}_i^{[i]})) + \phi_{cc}(\boldsymbol{s}_{n-1} - \boldsymbol{s}_{n-1}^{[n]}) \tag{47}$$

The formulation of p_0 only includes the objective function. It is with respect to $\boldsymbol{s}_1$, $\boldsymbol{s}_2$,…, $\boldsymbol{s}_{n-1}$, and solved with fixed $\boldsymbol{s}_1^{[1]}$, $\boldsymbol{s}_{i-1}^{[i]}$, $\boldsymbol{s}_i^{[i]}$, and $\boldsymbol{s}_{n-1}^{[n]}$. The objective function of p_0 only contains the augmented Lagrangian relaxation terms that are utilized to coordinate the key links between related elements.

When all the decomposed elements are formulated, the energy-optimal SMS allocation problem can be handled based on the steps depicted in part 2.2.

5 Case study

A case composed of five tasks [48] is used to verify the effectiveness and efficiency of ALC method in performing energy-optimal SMS allocation in this section. The information about tasks and candidate SMSs is listed in Table 4.

Table 4 Information about tasks and candidate SMSs

Task	SMS (O_i^j)	$t_{i.j}$	$c_{i.j}$	$e_{i.j}$	$t(i.j,(i-1).k)$	$c(i.j,(i-1).k)$
Task 1	O_1^1	9	15	10	--	--
	O_1^2	8	14	15	--	--
	O_1^3	10	15	13	--	--
Task 2	O_2^1	18	54	20	$t(2.1,1.1)$ 5	$c(2.1,1.1)$ 10
					$t(2.1,1.2)$ 3	$c(2.1,1.2)$ 9
					$t(2.1,1.3)$ 8	$c(2.1,1.3)$ 16
	O_2^2	19	55	16	$t(2.2,1.1)$ 7	$c(2.2,1.1)$ 15
					$t(2.2,1.2)$ 4	$c(2.2,1.2)$ 12
					$t(2.2,1.3)$ 7	$c(2.2,1.3)$ 19
	O_2^3	18	60	18	$t(2.3,1.1)$ 8	$c(2.3,1.1)$ 17
					$t(2.3,1.2)$ 6	$c(2.3,1.2)$ 15
					$t(2.3,1.3)$ 10	$c(2.3,1.3)$ 21
Task 3	O_3^1	9	43	6	$t(3.1,2.1)$ 12	$c(3.1,2.1)$ 25
					$t(3.1,2.2)$ 7	$c(3.1,2.2)$ 12
					$t(3.1,2.3)$ 10	$c(3.1,2.3)$ 22
	O_3^2	8	50	9	$t(3.2,2.1)$ 13	$c(3.2,2.1)$ 28
					$t(3.2,2.2)$ 6	$c(3.2,2.2)$ 9
					$t(3.2,2.3)$ 12	$c(3.2,2.3)$ 26

Task 4	O_4^1	14	25	25	$t(4.1,3.1)$ 0	$c(4.1,3.1)$ 0
					$t(4.1,3.2)$ 0	$c(4.1,3.2)$ 0
	O_4^2	16	21	23	$t(4.2,3.1)$ 0	$c(4.2,3.1)$ 0
					$t(4.2,3.2)$ 0	$c(4.2,3.2)$ 0
	O_4^3	13	28	21	$t(4.3,3.1)$ 0	$c(4.3,3.1)$ 0
					$t(4.3,3.2)$ 0	$c(4.3,3.2)$ 0
Task 5	O_5^1	1	41	3	$t(5.1,4.1)$ 6	$c(5.1,4.1)$ 21
					$t(5.1,4.2)$ 3	$c(5.1,4.2)$ 15
					$t(5.1,4.3)$ 3	$c(5.1,4.3)$ 12
	O_5^2	3	39	6	$t(5.2,4.1)$ 9	$c(5.2,4.1)$ 24
					$t(5.2,4.2)$ 6	$c(5.2,4.2)$ 17
					$t(5.2,4.3)$ 5	$c(5.2,4.3)$ 15

5.1 Effectiveness of ALC in solving energy-optimal SMS allocation problem

In order to verify the effectiveness of ALC method in performing energy-optimal SMS allocation, a centralized optimization method (i.e. genetic algorithm (GA)) and two variants of the ALC method are executed in a same computing environment.

The software Matlab R2016a and a PC with 2.60 GHz CPU /4.0 GB RAM are used to execute the whole computing process. The weight coefficients are set as $w_t = 0.1$, $w_c = 0.6$, $w_e = 0.3$. T_{max}=90, C_{max}=290, and E_{max}=100. The maximum iteration time is set as 1000. All initial values of Lagrangian multiplier parameters and weight coefficients are set as 0.01. The termination tolerance is set as ε=10^{-2}. Each method runs 50 times.

Table 5 Optimal allocation results of SMSs

Task	Genetic algorithm (GA)				Distributed ALC				Centralized ALC			
	O_i^j	t_i^j	c_i^j	e_i^j	O_i^j	t_i^j	c_i^j	e_i^j	O_i^j	t_i^j	c_i^j	e_i^j
1	O_1^1	9	15	10	O_1^1	9	15	10	O_1^1	9	15	10
2	O_2^2	19	55	16	O_2^2	19	55	16	O_2^2	19	55	16
3	O_3^1	9	43	6	O_3^1	9	43	6	O_3^1	9	43	6
4	O_4^3	13	28	21	O_4^3	13	28	21	O_4^3	13	28	21
5	O_5^1	1	41	3	O_5^1	1	41	3	O_5^1	1	41	3
Value of Objective	0.7008				0.7008				0.7008			
Computation Time	3.03 mins				11 mins				8.7 mins (*1.68* mins)			

Table 5 contrasts the optimal results of energy-optimal SMS allocation obtained by GA and two variants of the ALC method. As can be seen from the table, distributed ALC and centralized ALC can achieve the same optimal allocation results (i.e. SMS options, value of the objective function) as the GA method. However, the two variants of ALC method take much longer computation time than the GA method, i.e. distributed ALC and centralized ALC spend 11 mins and 8.7 mins, respectively, whereas GA just uses 3.03 mins to perform the whole optimization process. There are two major reasons to lead to this phenomenon. Firstly, complex key links are identified in the decomposed elements. Hence, a lot of auxiliary variables are introduced to the formulation of each decomposed element, which will impose conspicuous challenge on the computation efficiency of completing the whole optimization process. Secondly, ALC is recognized as a distributed optimization method. The required computing environment to implement this method should be parallel and distributed. However, in this research, all optimization processes are completed in a single PC. For making a better comparison, the computation time of the centralized ALC method is re-calculated with a parallel and distributed manner. In this circumstance, the whole computation time is the sum of computation time of master element p_0 and maximum computation time of the five decomposed elements p_1, p_2, p_3, p_4, and p_5. Then, the computation time of centralized ALC is calculated as 1.68 mins. Therefore, the computing efficiency of the ALC method will be well enhanced when the whole computing process is executed in a real parallel and distributed environment.

5.2 Performance analysis of ALC method

This primary goal of this part is to analyze the performance of ALC method in dealing with the energy-optimal SMS allocation problem. The analysis consists of two aspects. The first aspect is about the convergence performance of the ALC method. The second aspect is about the performance of the rate of getting the optimal result. For better illustration, the circumstances of termination tolerance $\varepsilon=10^{-3}$, $\varepsilon=10^{-4}$, and $\varepsilon=10^{-5}$ are investigated in this section.

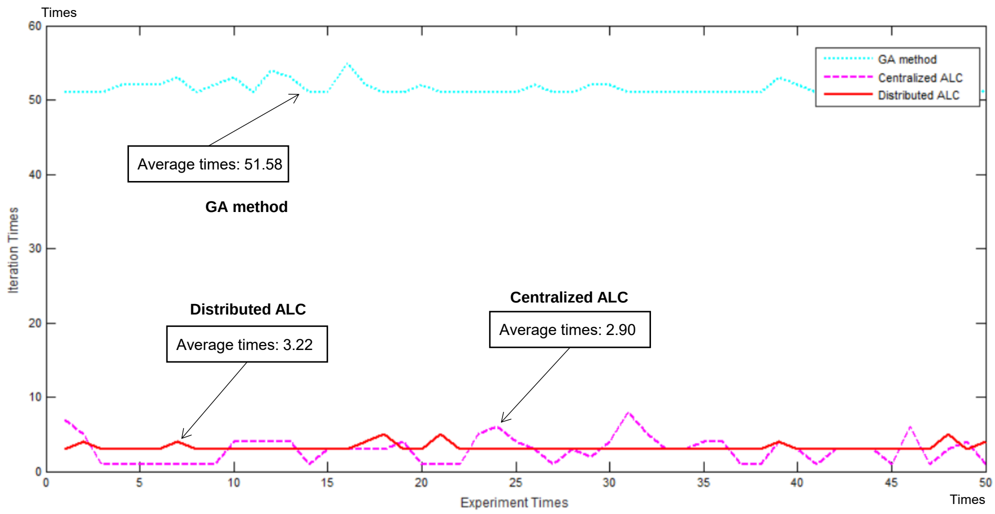

Fig. 6. Iteration times for $\varepsilon=10^{-3}$

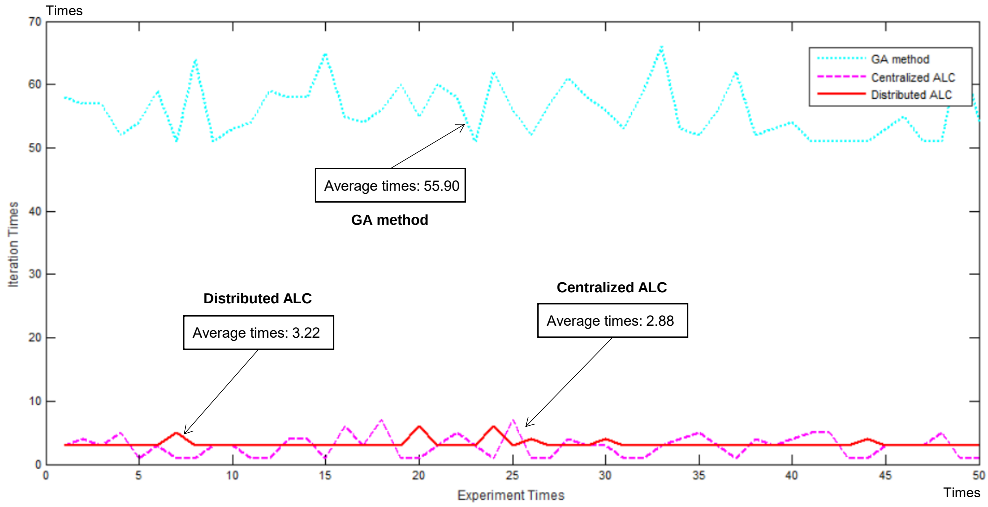

Fig. 7. Iteration times for $\varepsilon = 10^{-4}$

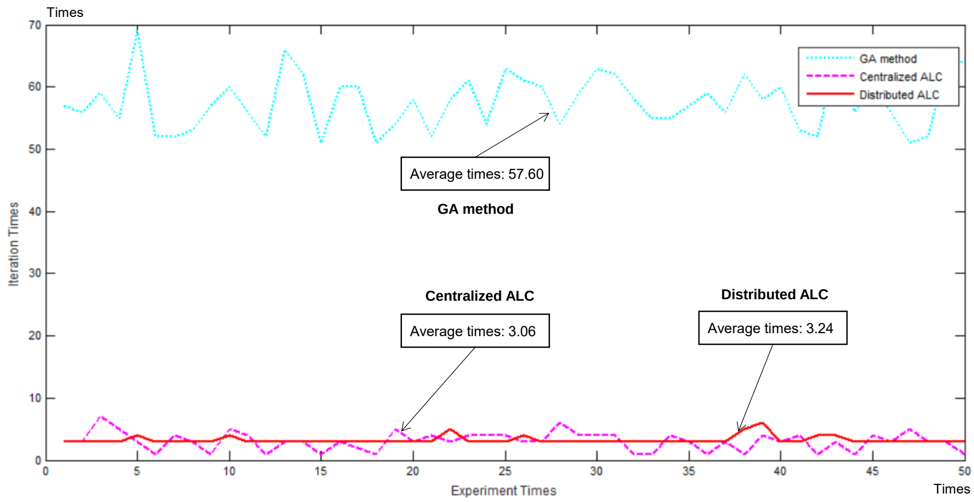

Fig. 8. Iteration times for $\varepsilon = 10^{-5}$

The iteration times of the whole optimization process being finished is used to evaluate the convergence performance of each method. Regarding different termination tolerances, iteration times of the GA method and two variants of the ALC method in solving the energy-optimal SMS allocation problem are compared in Fig. 6, Fig. 7, and Fig. 8. As shown in Fig. 6, when the termination tolerance is set as ε=10^{-3}, the average iteration times of the GA method, distributed ALC, and centralized ALC running fifty times are 51.58, 3.22, and 2.90, respectively. As shown in Fig. 7, when the termination tolerance is set as ε=10^{-4}, the average iteration times of the GA method, distributed ALC, and centralized ALC running fifty times are 55.90, 3.22, and 2.88, respectively. As shown in Fig. 8, when the termination tolerance is set as ε=10^{-5}, the average iteration times of the GA method, distributed ALC, and centralized ALC running fifty times are 57.60, 3.22, and 2.90, respectively. It can be seen that the GA method needs more iteration times than the two variants of the ALC method to complete the whole process. Thus, the ALC method has better convergence performance in solving the energy-optimal SMS allocation problem.

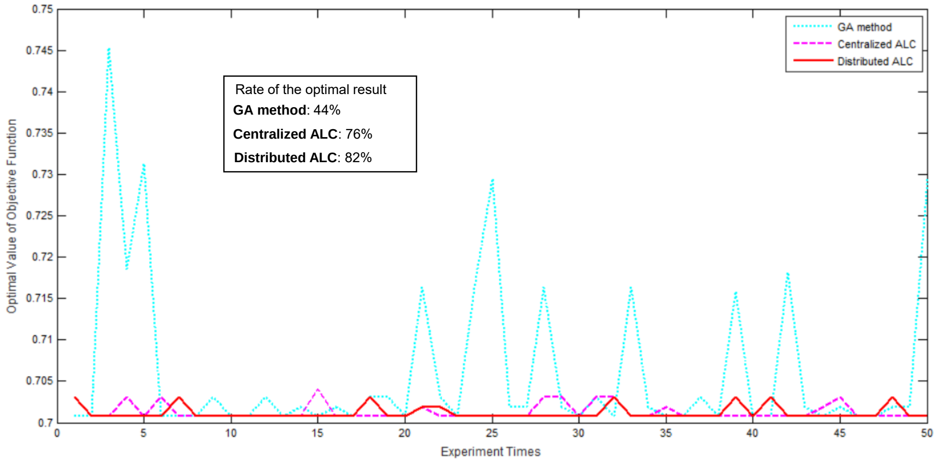

Fig. 9. Rate of getting the optimal result ($\varepsilon = 10^{-3}$)

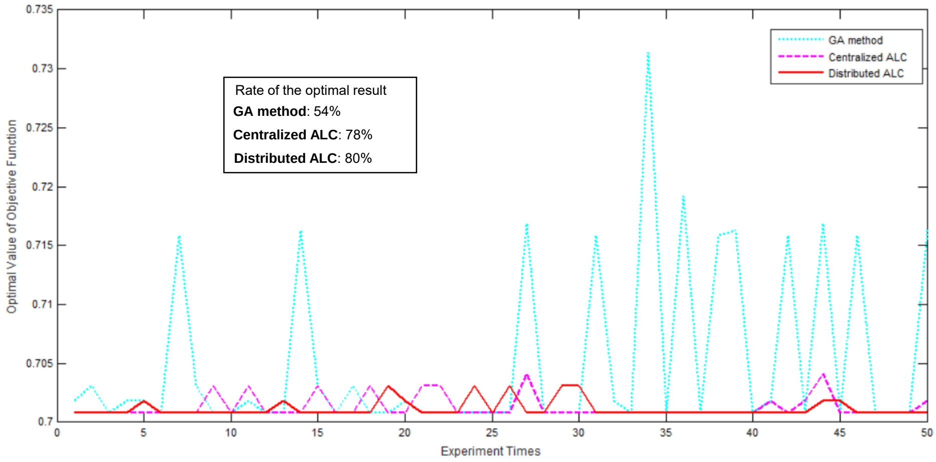

Fig. 10. Rate of getting the optimal result ($\varepsilon = 10^{-4}$)

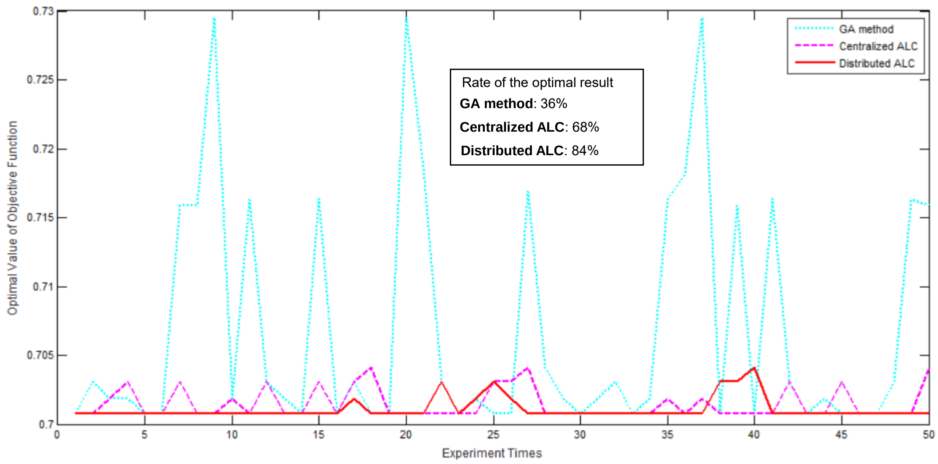

Fig. 11. Rate of getting the optimal result ($\varepsilon = 10^{-5}$)

As mentioned in section 5.1, the known optimization result of the energy-optimal SMS allocation problem is 0.7008. Regarding different termination tolerances, the rates of the GA method and two variants of the ALC method getting the known optimal result are compared in Fig. 9, Fig. 10, and Fig. 11. As shown in Fig. 9, when the termination tolerance is set as ε=10^{-3}, the rates of GA, distributed ALC, and centralized ALC getting the optimal result are 44%, 82%, and 76%, respectively. As shown in Fig. 10, when the termination tolerance is set as $\varepsilon=10^{-4}$, the rates of GA, distributed ALC, and centralized ALC getting the optimal result are 54%, 80%, and 78%, respectively. As shown in Fig. 11, when the termination tolerance is set as $\varepsilon=10^{-5}$, the rates of GA, distributed ALC, and centralized ALC getting the optimal result are 36%, 84%, and 68%, respectively. It can be seen that the ALC method has a higher rate to get the known optimal result than the GA method. Thus, the ALC method is more reliable in solving the energy-optimal SMS allocation problem. In addition, as shown in Fig. 9, Fig. 10, and Fig. 11, the fluctuation range of the optimal value obtained by the GA method is much larger than the two variants of the ALC method, which indicates that the stability of the ALC method is better than the GA method to deal with the energy-optimal SMS allocation problem.

Overall, the ALC method demonstrates many promising advantages (e.g. reliability, stability) over the GA-based centralized optimization method in performing the energy-optimal SMS allocation.

The case study in this paper is used to show the potential advantages of ALC in solving the smart manufacturing service allocation problem by taking into account energy consumption. Despite the above advantages, there are still some limitations in the case study. Firstly, the SMS allocation problem considered in this case study not quite large. The performance analysis with reference to the problem size and problem scalability may be more convincible to prove the superiority of ALC method. Large-scale cases with more tasks, services, and variables should be be investigated in the future. Secondly, there are many alternative methods that can be used for solving the service allocation problems. More comparisons with other methods (e.g. particle swarm optimization, artificial bee colony algorithm) should be made in the following research to find more efficient methods and further verify the superiority of ALC method.

6 Conclusions

Smart manufacturing paradigms are supposed to provide a service-oriented, high-efficient and sustainable production manner for industrial enterprises, and their key technologies have gained wide attention from both academia and industry. SMS allocation acts as a crucial part in promoting cleaner production among these technologies. The primary purpose of this paper is to use the ALC method to perform the energy-optimal SMS allocation.

The major contributions of this research can be summarized into four aspects. Firstly, the workflow of SMS allocation is identified, based on which the mathematical model of SMS allocation was further constructed. In the constructed model, energy consumption was considered as an evaluation criterion to implement sustainable and smart manufacturing. Secondly, the distributed optimization mechanism was introduced to solve the energy-optimal SMS allocation problem by taking into account the multiple production domains/disciplines of manufacturing tasks. Thirdly, the proposed energy-optimal SMS allocation problem was formulated according to two variants of the ALC method, i.e. distributed ALC and centralized ALC. Fourthly, the effectiveness of the proposed method in performing the energy-optimal SMS allocation was verified by a case study which demonstrated that the ALC method could achieve the same allocation results as the GA-based centralized optimization method. In addition, it has been proved that the ALC method can achieve better performance in terms of performing energy-optimal SMS allocation.

Based on the abovementioned contributions, potential future work may embrace the following facets. Firstly, how to construct a more comprehensive mathematical model for energy-optimal SMS allocation? The mathematical model of this study just considers the tasks in a serial sequence. In practice, the tasks in parallel sequence or hybrid sequence can be a more complex circumstance. Secondly, how to design a sustainable mechanism to implement SMS allocation? When exceptions occur, necessary measures should be taken to ensure that the tasks can still be completed according to the customer's requirements. Thirdly, how to develop a platform to execute energy-optimal SMS allocation in real-life? A platform is needed to facilitate the transactions between stakeholders and monitor the real-time information during tasks being executed by related SMSs.

Acknowledgements

The authors wish to acknowledge the financial support from the National Nature Science Foundation of China (U2001201, 51875451, 51834006) and the 111 Project Grant (B13044)，the National Research Foundation (NRF) Singapore and Delta Electronics International (Singapore) Pte Ltd., under the Corporate Laboratory@ University Scheme (Ref. SCO-RP1; RCA-16/434) at Nanyang Technological University, Singapore.

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Declaration of interests

☒ The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

☐The authors declare the following financial interests/personal relationships which may be considered as potential competing interests:

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Geng Zhang: Conceptualization, Methodology, Writing - Original Draft.

Gang Wang: Formal analysis, Investigation, Data Curation.

Chun-Hsien Chen: Writing - Review & Editing, Supervision, Funding acquisition.

Xiangang Cao: Writing - Review & Editing, Funding acquisition.

Yingfeng Zhang: Conceptualization, Supervision, Funding acquisition.

Pai Zheng: Writing - Review & Editing