Electron Commer Res (2011) 11: 123–149
DOI 10.1007/s10660-010-9053-1

A generic coordination mechanism for lot-sizing in supply chains

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Published online: 11 September 2010

Abstract A new generic mechanism to coordinate decentral planning of a group of independent and self-interested decision makers, who are searching for an agreeable contract regarding multiple interdependent issues, in the case of asymmetric information is presented. The basic idea of the mechanism is that the group members cooperatively carry out an evolutionary search in the contract space. Therefore the $(1, \lambda)$-selection procedure, which is used in many evolutionary strategies, is combined with the Borda maximin voting rule, which has been applied successfully in group decision making. The proposed mechanism is realized, applied and evaluated for production coordination in a supply chain. A decentralized variant of the multi-level uncapacitated lot-sizing problem (MLULSP) is taken as the production model. For the evaluation 95 problem instances are generated based on MLULSP instances taken from the literature, with problem sizes varying from 5 to 500 items, from 12 to 52 periods. Experimental results show that the proposed mechanism is effective to determine fair cost distributions.

Keywords Coordination · Supply chain · Lot-sizing · Voting

1 Introduction and literature review

Coordination of decentral production planning in a supply chain (SC), i.e. the network of organizations involved in creating final customer products [20], can be a challenging task since the organizations or SC members are often independent of each other and are guided by individual and conflicting objectives [79]. In such a case the SC members are not willing to share private planning information, e.g. cost

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parameters [21]. Thus, coordination mechanisms (CMs) are needed which enable the SC members to design contracts [16], i.e. agreements on joint production decisions, considering given asymmetric information [81].

Different types of objectives for group decision problems are distinguished in the literature (e.g. [19]) and thus are used to evaluate the performance of CMs. On the one hand efficiency criteria, e.g. Pareto efficiency and social efficiency, are used. On the other hand objective criteria are suggested which offer a level of fairness. Fairness is often defined on the basis of some sets of axioms and principles [5, 14, 33, 66, 67]. Two fairness criteria are often used: the Nash bargaining criterion and the Rawls's maximin criterion. The first criterion is based on the four axioms defined by Nash [68]. The second criterion is based on Rawls's two principles of justice [73] and has clear egalitarian implications. It maximizes the welfare level of the worst-off group member. It is one of the most well-studied notions of fairness in the context of allocation problems (e.g. [47, 57, 64]). In group decisions there is often an inherent conflict between social efficiency and fairness (e.g. [65]).

An overview of CMs for production planning in a SC considering asymmetric information is given by Stadtler [79]. The author identifies three directions for future research. (1) The development of CMs which are generic with regard to the kind of contract under consideration and thus applicable for many coordination problems. (2) The development of CMs which can be used for determining complex contracts, i.e. contracts which contain values for multiple interdependent decision variables. Most existing CMs are designed to compute contracts for coordination problems consisting of only independent or a few interdependent decision variables. (3) The development of CMs which address, support or even secure a fair distribution of gains or costs among SC members in order to increase their willingness to use and to accept the CM (see also [3]). Social efficiency is the dominant objective of most existing CMs for SC planning [79]. In these approaches social welfare is often measured by the total or average costs (e.g. [8, 30, 36, 59]) or the total profit (e.g. [17]) of the entire SC. Only a few CMs search for fair solutions (e.g. [18, 34, 41, 42]).

In order to resolve objective conflicts in group decision problems which consists of multiple interdependent decision variables considering asymmetric information, often approaches are suggested which relate to single text negotiation [31, 32, 36–40, 46, 50, 52–55, 61, 72]. These approaches[1] use a mediator which repeatedly generates contract proposals. In this manner these approaches differ from 'typical' negotiations which are characterized by an exchange of offers between the parties involved. For a classification of (electronic and automated) negotiation we refer to Jennings et al. [48, 49], Bichler et al. [11], Kersten [51], Lomuscio et al. [62], Sandholm [77], and Ströbel and Weinhardt [82]. The generation of proposals has to be carried out in an unbiased manner and without any specific knowledge about the individual objective functions of the group members [36]. A generated proposal is rejected or accepted as a tentative contract by the mediator taking the preferences of all group members into account. In this way a joint search in the contract space is executed. Different options for the generation and the acceptance of proposals are suggested.

[1] These mediator-based coordination mechanisms are often referred to as "multi-party negotiation" [31], "electronic negotiation" [37], "mediating multi-issue negotiation" [63], and "multi-issue negotiation" [49] in the literature.

- Procedures to generate proposals are: (1) Random generation of proposals by small changes of previous accepted contracts [36–38, 52–55], (2) recombination of fragments of previously accepted contracts [60, 61, 83], and (3) computation of improving search directions by means of gradient search methods [31, 32]. The last generation procedure requires continuous decision variables.
- Rules to accept proposals are: (1) Exclusive acceptance of improving proposals (e.g. [31, 32]). This rule may result in a coordination process that gets stuck rather soon [52]. (2) Temporary acceptance of inferior proposals with a time-decreasing probability. This acceptance rule often results in superior final contracts (e.g. [50, 52]). The acceptance probability can be computed either by each group member [36, 53] or by the mediator [52]. However, the first option may result in a prisoner's dilemma [36].

Most of the mentioned mediator-based CMs are designed to compute a social efficient solution (e.g. [36, 50, 52–55]). Only a few approaches aim to compute fair solutions (e.g. [32, 61]). The objective of this paper is to design and analyze a new mediator-based CM for determining complex contracts considering given asymmetric information. The CM should be applicable for multiple decentral production planning or SC scenarios and be able to compute balanced and thus fair distributions of gains or costs among the SC members.

In order to study the effectiveness of the new CM the multi-level uncapacitated lot-sizing problem (MLULSP) is chosen. Lot-sizing in a SC is a major driver of costs and therefore is among the most widely researched areas in operational SC management [59, 79]. The MLULSP captures some essential issues of production problems, namely several final products, a multi-level process structure, and the fundamental trade-off between setup and inventory [25, 71]. This model is often applied in material requirements planning systems and is therefore of practical importance [87]. The MLULSP is a monolithic model, i.e. it assumes one central decision maker and that all planning information is public. To frame the MLULSP as a group decision problem, we follow the idea of Ertogral and Wu [34], and Dudek [29], and use a facility-based decomposition of the MLULSP. Note that the mentioned authors resort to the multi-level multi-item capacitated lot-sizing problem (MLCLSP). The reason to choose the MLULSP is two-fold.

(1) A multitude of large problem instances and solutions for the MLULSP are reported in the literature which allows a meaningful evaluation of planning methods.
(2) In case of the MLULSP the feasibility of solutions can be guaranteed in an easy way ([25], see also Sect. 4.2), i.e. without any heuristics. This enables the free evolvement of CMs regarding the generation and acceptance of solutions or production plans. Thus, the performance of CMs is not influenced by heuristics that are necessary to generate feasible solutions.

The feature described in (1) is also true for the MLCLSP, which is used by Ertogral and Wu [34], Dudek [28], and Dudek and Stadtler [29, 30]. However, this does not apply for (2) because even finding a feasible solution for the MLCLSP is *NP*-complete [63]. This motivates the use of the MLULSP in addition to the MLCLSP as a basis to evaluate the performance of CMs.

The reformulated MLULSP can be described as follows. External demands over a T-period time horizon and a bill-of-material (BOM) structure are given for each final customer product. The production of subassemblies and components is spread across multiple independent facilities. From a contractual perspective a separation between cost-based scheduling decisions and the setting of transfer prices between facilities, which would then determine individual revenues, is assumed. Moreover, the assumption is made that transfer prices are set in a way that revenues between the facilities are (approximately) equal. Based on these assumptions the following coordination problem takes only the determination of cost-based scheduling decisions into account. Constant cost parameters, namely setup costs per production run and inventory holding costs per unit per period, are given for each item in the BOMs. Each facility pursues the individual objective to minimize its sum of setup and inventory holding costs, which are referred to as 'local costs'. Since the facilities have different cost parameter values they prefer different production plans or solutions, i.e. there is a conflict of interest. The objective of coordination is to find a production plan that minimizes the local costs of the worst-off facility according to the Rawls's criterion. This objective is motivated by the intention to find a solution where the total costs are balanced between the facilities. Due to the assumption, that the revenues of all facilities are approximately equal, a balanced cost distribution leads to a fair profit sharing among the facilities. The cost parameter values and the individual objectives represent private information of each facility. The restriction is that all external and dependent demands are met on time. A problem instance of the group decision problem is given in Table 1.

In Table 1 an example for a two-tier SC with two production facilities is given. Facility F_1 produces the final customer product (item 1), and facility F_2 supplies the necessary component (item 2). External demands (in units) for item 1 for each period t of the 4-period planning horizon, and cost parameters (in monetary units—MU) for both items are given. The range of the cost parameters are set according to the cost values used by Coleman and McKnew [22]. The production of item 1 triggers a dependent demand of item 2. It is assumed that one unit of item 2 is necessary to produce one unit of item 1, and that all lead times for production and purchasing are zero. Moreover, starting inventory is assumed to be zero, and backlogging is not allowed.

As shown by Veinott [84] the MLULSP has the fundamental property that any optimal lot-size must cover an integer number of future demands. This property allows deriving optimal lot-sizes from optimal setup decisions [25, 75]. 64 alternative feasible solutions with regard to the setup decisions exist for the example described above.

Table 1 Example of a problem instance

Facility	External demand				Product structure	Setup costs per production run	Holding costs per unit per period
	$t=1$	$t=2$	$t=3$	$t=4$			
F_1	80	100	20	120	1	1.00	0.11
F_2	–	–	–	–	2	10.50	0.07

Table 2 Example of four solutions

Facility	Setup in period t				Lot-size in period t				Setup costs	Holding costs	Local costs	Max. local costs	Total costs
	1	2	3	4	1	2	3	4					
												solution 1	
F_1	1	1	1	1	80	100	20	120	4.0	0.0	**4.0**	30.8	34.8
F_2	1	0	0	1	200	0	0	120	21.0	9.8	30.8		
												solution 2	
F_1	1	1	0	1	80	120	0	120	3.0	2.2	5.2	29.4	**34.6**
F_2	1	0	0	1	200	0	0	120	21.0	8.4	29.4		
												solution 3	
F_1	1	0	0	1	200	0	0	120	2.0	15.4	17.4	**21.0**	38.4
F_2	1	0	0	1	200	0	0	120	21.0	0.0	21.0		
												solution 4	
F_1	1	0	0	0	320	0	0	0	1.0	55.0	56.0	56.0	66.5
F_2	1	0	0	0	320	0	0	0	10.5	0.0	**10.5**		

The feasibility of a solution requires a setup in period $t = 1$ in order to produce the customer demand of that period. Four of the 64 solutions are shown in Table 2.

For each solution shown in Table 2 the setup decisions, the lot-sizes and the costs per facility are given. The lot-sizes are derived according to Salomon and Kuik [75]. Whenever a setup is made the lot-size is equal to the sum of the demand in the current period and the demands in all subsequent periods in which there is no setup. Facility F_1 prefers the solution 1 (production of item 1 in each period) which minimizes the local costs of F_1. In contrast to this, facility F_2 prefers the solution 4 in which all holding costs are transferred to facility F_1. Thus, there is a considerable conflict of interest between the facilities. Solution 2 is the social efficient solution which minimizes the total costs of both facilities. However, solution 3 is the fairest solution, which minimizes the local costs of the worst-off facility (here facility F_2). As shown, the total costs are more balanced in solution 3 than in other solutions. The comparison of solutions 2 and 3 brings out the conflict between social efficiency and fairness. All four solutions are Pareto efficient. All 64 solutions are shown in Fig. 1 in a two-dimensional diagram using the costs of both facilities as axes (some dots represent multiple solutions).

Obviously, most real-world SC settings involve more intricate characteristics than the reformulated MLULSP: e.g. capacitated production (e.g. [28]), SC members with several business functions [79], and the negotiation of unit prices and transfer prices (e.g. [6, 41]). Thus, applying the reformulated MLULSP in practical SC planning situations is limited. However, it is an appropriate benchmark problem for studying the performance of CMs because it incorporates essential features which makes the coordination in particular difficult: asymmetric information, considerable objective conflicts, multiple interdependent decision variables, and *NP*-hardness (in the case of general production structures, see [4]). These features can be found in most

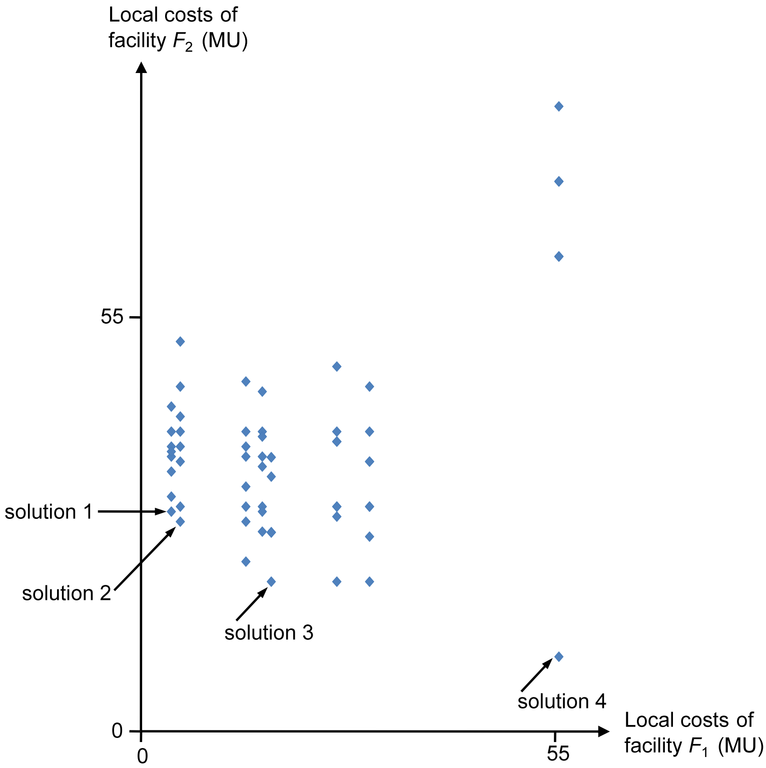


Fig. 1 Quality of solutions

real-world SC scenarios. In this way the reformulated MLULSP is a representative example of coordination problems in decentralized production planning.

The MLULSP and its reformulation are described in Sect. 2. In Sect. 3 the new mediator-based CM is described. The adaption of the mechanism for solving the considered problem is described in Sect. 4. In Sect. 5 the performance of the new mechanism is analyzed and compared with other solution methods. Section 6 contains discussion and some recommendations for future work.

2 Decentralized multi-level uncapacitated lot-sizing

2.1 The multi-level uncapacitated lot-sizing problem

Based on the model formulation by Steinberg and Napier [80], the MLULSP is represented as a mixed-integer program in the following. Therefore, the notation as described in Table 3 is used.

Table 3 Notation of the MLULSP

Parameters	
N	number of items
I	set of items; $I = \{1, \ldots, N\}$
T	number of periods
$\Gamma(i)$	all direct successors of item i
$\Gamma^{-1}(i)$	all direct predecessors of item i
s_i	setup costs for item i (in monetary units)
h_i	inventory holding costs for item i (in monetary units per item unit and per period)
$d_{i,t}$	external demand for item i in period t (in production units) if i is a final product ($\Gamma(i) = \varnothing$)
$r_{i,j}$	production ratio, i.e. the quantity of item i required to produce one unit of item j
t_i	lead time required to assemble, manufacture, or purchase item i
M	a large number
Variables	
$x_{i,t}$	amount of production (lot-size) for item i at the beginning of period t
$l_{i,t}$	amount of inventory for item i at the end of period t
$y_{i,t}$	binary (setup) variable which indicates if an item i is produced in period t ($y_{i,t} = 1$) or not ($y_{i,t} = 0$)
$d_{i,t}$	dependent demand for item i in period t (in production units) if i is not a final product ($\Gamma(i) \neq \varnothing$)

By using the notation given above, the MLULSP is modeled according to Yelle [91] and Dellaert and Jeunet [26]:

$$\min \quad \sum_{i=1}^{N} \sum_{t=1}^{T} s_i y_{i,t} + h_i l_{i,t}, \tag{1}$$

$$\text{subject to} \quad l_{i,t} = l_{i,t-1} + x_{i,t} - d_{i,t}, \quad i = 1, \ldots, N, \text{ and } t = 1, \ldots, T, \tag{2}$$

$$d_{i,t} = \sum_{j \in \Gamma(i)} r_{i,j} x_{j,t+t_i}, \quad \forall i | \Gamma(i) \neq \varnothing, \text{ and } t = 1, \ldots, T, \tag{3}$$

$$x_{i,t} - M y_{i,t} \leq 0, \quad i = 1, \ldots, N, \text{ and } t = 1, \ldots, T, \tag{4}$$

$$l_{i,t} \geq 0, \quad i = 1, \ldots, N, \text{ and } t = 1, \ldots, T, \tag{5}$$

$$x_{i,t} \geq 0, \quad i = 1, \ldots, N, \text{ and } t = 1, \ldots, T, \tag{6}$$

$$y_{i,t} \in \{0, 1\}, \quad i = 1, \ldots, N, \text{ and } t = 1, \ldots, T. \tag{7}$$

The objective function (1) is the total cost *TC*, i.e. the sum of setup and inventory costs for all items over the entire planning horizon. Equation (2) is the inventory balance equation. $I_{i,0}$ represents starting inventory levels. Constraint (3) ensures that a lot of item j in period $t + t_i$ triggers a corresponding dependent demand $d_{i,t}$ in each predecessor item $i, i \in \Gamma^{-1}(j)$. Constraint (4) guarantees that a setup cost will be incurred when a batch is purchased or produced. The constraints (5) and (6) are the non-negativity constraints on inventory and production variables. Finally, constraint (7) represents the binary character of decisions on setups. Arkin et al. [4] show that the MLULSP is *NP*-hard for general multi-level product structures, i.e. for product structures, where each item can have more than one successor and predecessor [75].

2.2 A decentralized model extension

The MLULSP is now framed as a group decision model by introducing a decomposition of I in n disjoint subsets $F_k \subset I$, $k = 1, \ldots, n$, $\bigcup_k F_k = I$. F_k represents a facility, which produces all included items. The number of items produced by facility F_k is denoted by NF_k, $NF_k = |F_k|$. The problem structure resulting from the decomposition can be non-cyclic or cyclic [34]. In Fig. 2 both alternatives are shown in an example. This form of graphical representation of the problem, as chosen in Fig. 2, follows the literature [12].

The production dependency in Fig. 2 is shown by the arrows between items. Items are sorted in increasing level numbers and each common part is listed at the lowest level at which it is used anywhere in the product structure [25].

Moreover, a group $A = \{ag_1, \ldots, ag_n\}$ of autonomous decision agents (in short: agents) is given. Agent $ag_k \in A$ is assigned to facility F_k. For example, agent ag_k can represent a company, which owns facility F_k. The agents are self-interested. Agent ag_k has the objective to minimize the local costs C_k according to

$$C_k = \sum_{i \in F_k} \sum_{t=1}^{T} s_i y_{i,t} + h_i l_{i,t}, \quad k = 1, \ldots, n. \tag{8}$$

In the following, the function (8) is also denoted as the individual or local evaluation function of agent ag_k. However, the single objectives of the agents are usually conflicting. In this case the local costs C_k, $k = 1, \ldots, n$, cannot be minimized simultaneously. Therefore Pareto efficient solutions are sought. Among these, solutions in which total costs are more balanced between agents and which are thus fairer than

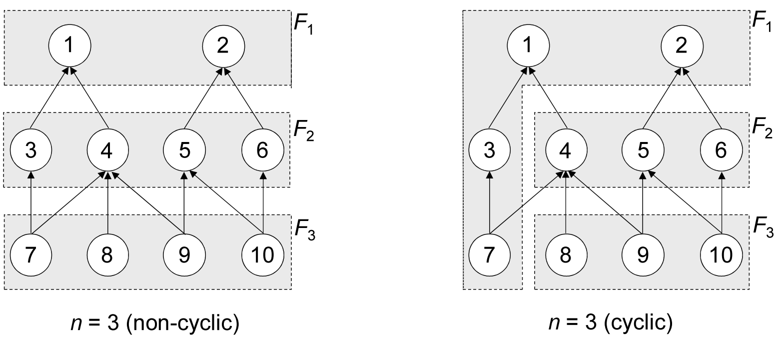


Fig. 2 Problem structure

other solutions are of interest. To measure fairness the Rawls's criterion is applied according to

$$\min \max_{k=1,\ldots,n} C_k. \tag{9}$$

In the objective function (9) the expression $\max_{k=1,\ldots,n} C_k$ represents the maximum local costs MC of a solution. Thus, the group decision making process is guided by the objective of minimizing the local costs of the agent who is worst-off.

With regard to the distribution of the planning information, the following three assumptions are made: (1) The cost parameters s_i and h_i, $\forall i \in F_k, k = 1, \ldots, n$, are private, i.e. they are only known to the agent ag_k (asymmetric information). (2) Agent ag_k does not announce its local costs (asymmetric information). (3) The product structures are known by all agents (symmetric information). This assumption is justified if the companies running the facilities also work together in a strategic way, e.g. by jointly developing the final products (collaborative engineering).

3 A generic coordination mechanism

A new generic mediator-based CM will be described to coordinate the decision making between n independent and self-interested group members or agents taking asymmetric information into account. The mechanism combines the effective selection procedure used in $(1, \lambda)$-evolution strategies and voting rules used in group decision making.

Evolution strategies (ESs) belong to the class of evolutionary algorithms (EAs) [10, 74, 78, 90]. For combinatorial optimization problems often the $(1, \lambda)$-ES is suggested [69]. This iterative search method is based on the following idea. At the beginning of the search an initial individual is generated, which represents a solution of the optimization problem at hand, Three steps are carried out in each iteration: (1) A set of λ individuals, referred to as offspring, is generated by mutation of the current individual. (2) The offspring are evaluated and the best individual regarding to a given fitness function is selected. (3) The current individual is replaced by the selected offspring individual. The quotient $1/\lambda$ is called selective pressure, where a small value indicates a high selective pressure and vice versa [70].

Voting is a key method in group decision making to aggregate conflicting preferences [76, 88]. In a voting scenario, there is a set of candidate outcomes (here contract proposals) over which the voters express their preferences by submitting a vote (often a ranking of the candidates), and the winner is determined based on these votes. A voting rule maps a vector of the n voters' votes to one of the candidates (the winner) in the candidate set. Voting rules such as Borda count, Borda maximin, approval, and the Hare system are often applied [23, 24]. Combining the concept of ES and voting leads to a new mediator-based CM. This new mechanism, which is referred to as ES-CM in the following, is described in Fig. 3.

The mediator manages the contract c and repeatedly generates new contract proposals (the offspring OFF). The proposal generation to be carried out by the mediator is based on the mutation approach of ESs. The agents evaluate the generated proposals by their objective functions and cooperatively select one proposal $pr \in OFF$

input: λ; *maxr*;

mediator: generate a set *OFF* of λ initial contract proposals randomly;
each agent ag_k: evaluate all proposals in *OFF* using the private objective function of ag_k;
all agents: select one proposal *pr* from *OFF* by a group decision using a voting rule;
mediator: initialize the contract *c* by the selected proposal: $c := pr$;
mediator: initialize the round counter: $rd := 0$;
WHILE ($rd < maxr$)
    mediator: initialize the set *OFF* of contract proposals: $OFF := \varnothing$;
    WHILE (NOT λ proposals have been generated)
        mediator: generate a new contract proposal *pr* from *c* by mutation;
        mediator: update the offspring: $OFF := OFF \cup \{pr\}$;
    each agent ag_k: evaluate all proposals in *OFF* using the private objective function of ag_k;
    all agents: select one proposal *pr* from *OFF* by a group decision using a voting rule;
    mediator: IF (*pr* is preferred more than *c* by each agent) accept the selected proposal: $c := pr$;
        ELSE accept the selected proposal ($c := pr$) with a probability P_{acc};
    mediator: update round counter: $rd := rd + 1$;

output: the final contract *c*;

Fig. 3 The ES-CM

as a candidate for replacing the current contract *c*. Since the agents are not willing to announce their objective function values (private information), the selection and replacement steps (highlighted in grey in Fig. 3) differ considerably from the corresponding steps in ESs. The suggested modification of these steps is motivated as follows:

- The agents select one proposal $pr \in OFF$ by voting (see Sect. 4.3). Therefore, the agents will announce their preferences (but not their objective function values) for the proposals in *OFF* to the mediator. From the viewpoint of ESs the fitness function used here could be described as 'acceptability by the agents'. This step is motivated by a desire to determine a compromise search direction. The idea to determine compromise search directions has been suggested by Ehtamo et al. [31, 32]. However, this approach differs considerably from ES-CM (see Sect. 6).
- The acceptance of *pr* as a tentative contract *c* depends on the preferences of the agents for *pr* and *c*. Two cases can be distinguished. Firstly, *pr* is preferred more than *c* by each agent. An agent prefers *pr* more than *c*, if and only if it is not worse than the current contract *c* with regard to the objective function of the agent. Secondly, at least one agent does not prefer *pr* more than *c*. An agent does not prefer *pr*, if *pr* is worse than *c* with regard to the objective function of the agent. A selected proposal which is not preferred by each agent is referred to as an 'inferior proposal'. As shown in Fig. 3, the current contract *c* is always replaced by the

selected proposal *pr*, i.e. *pr* is accepted, if it is preferred by each agent. Moreover, inferior proposals are also accepted with a probability P_{acc} which is decreased during the rounds or the execution time and which depends on the number $\bar{n}$ of agents that not prefer *pr*

$$P_{\text{acc}} = \frac{maxr - 1 - rd}{maxr - 1} \times \frac{n - \bar{n} + 1}{n}. \tag{10}$$

The temporary acceptance of inferior proposals is motivated by desire to avoid an early stagnation of the search. The decrease of the probability P_{acc} during the time is necessary to achieve a convergence. The idea of using a time-decreasing probability to accept inferior proposals during the search has been suggested by Klein et al. [53], and Fink [36, 37]. However, these approaches differ considerably from ES-CM (see Sect. 6).

As with other mediator-based CMs (e.g. [36]) ES-CM is generic, i.e. contract independent. To select a generated proposal, no information about the private evaluation or objective functions of the agents is needed. In order to realize and apply the mechanism for a specific problem (e.g. the reformulated MLULSP), contracts have to be formally specified, and a mutation operator, which allows the generation of feasible proposals, has to be developed. Moreover, a voting rule has to be chosen.

4 Realization of the coordination mechanism

4.1 Representation of contracts

The set of feasible solutions of the MLULSP constitutes the given contract space. A contract can basically be understood as an $N \times T$ matrix, in which the lot-size $x_{i,t}$ is given for each item and each period. In order to generate feasible solutions for the MLULSP an indirect problem representation is dealt with in this article [25]. It should be remarked that Fink [38] also generates contracts on the basis of an encoding.

A redundant binary encoding is chosen to represent contracts [44]. An encoded contract c consists of a $N \times T$ bit matrix, in which exactly T bits are reserved for each item. The bit $c_{i,t}$, $i = 1, \dots, N$, and $t = 1, \dots, T$, represents a preselection of periods that can be used when required for production, where $c_{i,t} = 1$ when period t is preselected as a 'possible' production period for item i, and $c_{i,t} = 0$ otherwise.

Decoding an encoded solution is described in Homberger [44]. The decoding procedure can be roughly described as follows: The lines of a given encoded contract c are run through consecutively in ascending order of the line numbers. Two decoding steps are carried out for each line or item i:

- Firstly, for each period t, $t = 1, \dots, T$, the demand $d_{i,t}$ is determined. The demand is exogenously given for final products, but it is calculated based on (3) for intermediate products and components.
- Secondly, for each period t, $t = 1, \dots, T$, the stored quantity $l_{i,t}$, the setup decision $y_{i,t}$, and the lot-size $x_{i,t}$ are computed. For this purpose, for each period t a check is made to determine whether a demand $d_{i,t}$, $d_{i,t} > 0$, is given. Two cases can be distinguished for selecting the setup $y_{i,t}$: (a) The period t in the encoded

solution c is preselected ($c_{i,t} = 1$). The demand $d_{i,t}$ is then produced in period t; i.e. $y_{i,t}$ is set to 1, and $x_{i,t}$ is actualized as follows: $x_{i,t} := x_{i,t} + d_{i,t}$. (b) The period t is not preselected ($c_{i,t} = 0$). Then a lot is run in period w ($w < t$, $c_{i,w} = 1$), which is the last period before t and which is preselected for the production of i in solution c. The quantity $d_{i,t}$ produced in period w is stored until period t, i.e. $y_{i,w}$ is set to 1, $y_{i,t}$ is set to 0, and $x_{i,w}$ is updated as follows: $x_{i,w} := x_{i,w} + d_{i,t}$.

4.2 Initialization and mutation of contracts

The initialization and mutation of encoded contract proposals are based on the procedures described by Homberger [44].

To generate an initial encoded contract proposal at the beginning of the coordination process, bits with probability 0.5 are set to zero, and otherwise to one. To ensure the generation of feasible contract proposals, bits regarding to the first demands of the items are initialized to one and remain unchanged during the search [25].

Two mutation operators are used alternatively to modify a given encoded contract proposal: a flip-mutation, and a swap-mutation. In each case bits are varied with probability $P_{\text{mut}} = 1/(T \times N)$ in dependency on the problem size [7].

4.3 Voting-based selection

In each round of the coordination process the agents jointly select one proposal *pr* from the offspring set *OFF*. Therefore the agents make a group decision by voting. The Borda maximin rule is used as the voting rule. This rule is very egalitarian [13] since it maximizes the rank of the agent who is worst off by selecting the proposal *pr*. It is implemented as a stepwise procedure. In each voting step every agent ag_k selects exactly one proposal $pr \in OFF$ and relays the vote to the mediator. The set of proposals for which agent ag_k has not voted yet is denoted as $VLIST_k \subseteq OFF$. An agent ag_k may vote for exactly one proposal $pr \in VLIST_k$. Agent ag_k rationally selects the proposal from $VLIST_k$ for which it gets the best objective function value in the local objective function (see (8)). As soon as all agents have cast their votes in a voting step, the mediator proves if a proposal $pr \in OFF$ exists which got one vote from each agent. Assuming that a proposal like that exists, it will be selected and the selection process is completed. The first proposal to receive a vote from each agent is obviously the alternative for which the worst rank (across all agents) is best.

In Fig. 4 the voting-based selection of a proposal is presented. It is assumed that agent ag_1 (ag_2) ranks the contract proposals from best to worst as follows: $pr_5, pr_1, pr_4, pr_2, pr_6, pr_3$ ($pr_3, pr_2, pr_1, pr_6, pr_5, pr_4$).

In the example of Fig. 4 three voting steps are taken one after another. After the completion of the voting step 3 the proposal pr_1 has received exactly one vote from each of the two agents and therefore it will be selected.

The described voting rule was extended to consider the following special cases:

- If $VLIST_k$ contains q, $q > 1$, proposals with the same minimum local costs for agent ag_k, the agent will cast a vote for each of these proposals. In this case, agent ag_k cannot cast another vote in the following $q - 1$ voting steps.

Fig. 4 Example of voting

	First step		Second step		Third step	
	ag_1	ag_2	ag_1	ag_2	ag_1	ag_2
pr_1			1		1	1
pr_2				1		1
pr_3		1		1		1
pr_4					1	
pr_5	1		1		1	
pr_6						

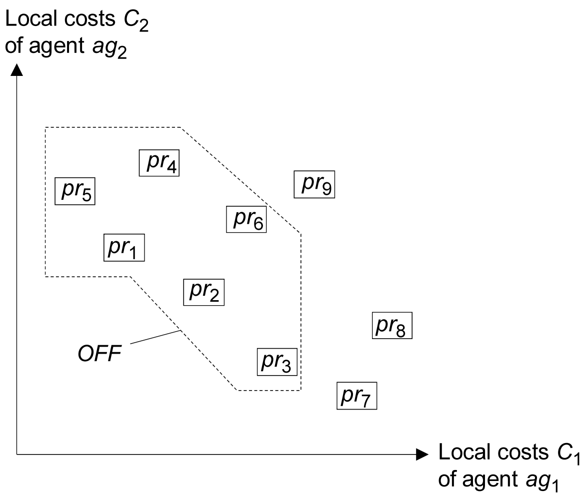


Fig. 5 Example of a contract space

- After all agents have cast a vote in a voting step, it is possible that multiple proposals have received a vote from all agents. In this case ties are broken by an equiprobable lottery on the set of tied proposals [27].

As a variant of the Borda voting rule, Borda maximin violates the axiom of independence of irrelevant alternatives (IIA) which holds that the social ranking of two candidates (contract proposals) should not be influenced by the placement of other candidates in the ballots (offspring *OFF*) of the voting agents [43, 56]. As a consequence of this the effectiveness of ES-CM to achieve a high solution quality can be decreased. This effect is clarified by an example in Fig. 5.

In Fig. 5 a contract space is shown which consists of the contracts $\{pr_1, \ldots, pr_9\}$. The selection of a solution from the set of all contracts, based on the Borda maximin rule, will determine the solution pr_2 as a winner. Now we consider two different situations for the iterative solution approach ES-CM, which is configured in this example with the parameter value $\lambda = 6$. In the first situation the set of generated offspring *OFF* consists of the contract proposals $\{pr_1, pr_2, pr_3, pr_4, pr_5, pr_6\}$ as shown in Fig. 5. The application of the Borda maximin rule will determine the solution pr_1 as a winner although the solution pr_2 is an element of *OFF* (see also the example used in Fig. 4). In the second situation it is assumed that *OFF* consists of the contract proposals $\{pr_1, pr_2, pr_3, pr_7, pr_8, pr_9\}$. The application of the Borda maximin rule will now determine the solution pr_3 as a winner although the solutions pr_1 and pr_2 are elements of *OFF*. The example shows that irrelevant proposals in *OFF* influence the selection and thus the determination of the search direction. Taking this effect into account and that usually different proposals are considered in each round, it cannot be expected that the ES-CM finds the solution pr_2 (winner, if all contracts are considered). However, this result should be put into perspective by consideration of the following issues. (1) The application of the Borda maximin rule to select one proposal *pr* from *OFF* is only a heuristic approach to determine a compromise search direction. Because of the complexity of the MLULSP it is not possible to generate all possible contracts or solutions in the case of larger problem instances in reasonable computation times. (2) The search direction is not only influenced by the voting rule (e.g. Borda maximin) but also by the acceptance decisions on the selected proposal *pr*. As described in Fig. 3 a selected proposal *pr* can be rejected by the agents.

It should be noted that it is assumed each agent will rank the proposals in *OFF* according to its true preferences. As mentioned by Ehtamo et al. [31] this assumption can be justified since information is incomplete and thus an untruthful declaration of preferences to the mediator can lead to 'backfires' in several ways (see also [15]). However, Vetschera [86] has shown that even for complex group decision methods, very simple strategies for manipulation of preference information can successful increase the possibility of unilateral improvements.

5 Computational results

5.1 Problem instances

Three classes of benchmark problems are suggested in the literature to evaluate methods for the MLULSP [25]. The classes differ from each other in particular with regard to the number N of items, the number T of periods to be planned, the product structure, the lead time t_i, the production ratio $r_{i,j}$, the cost parameters s_i and h_i, and the external demands $d_{i,t}$ for final customer products. A rudimentary description of the instances based on these parameters is given in Table 4.

In class 1 the cost parameters s_i and h_i are chosen such that setup costs increase and inventory holding costs decrease along any branch of the product structure (see

Table 4 Problem instances of the MLULSP

Class	No. of instances	N	T	Product structure	t_i	$r_{i,j}$	s_i	h_i	d_i	References
1	96	5	12	assembly	0	1	$[1.28, 50]$	$[0.05, 0.8]$	$[0, 270]$	[9, 22, 85]
2	40	40, 50	12, 24	assembly, general	0	1	$[50, 950]$	$[0.2, 4]$	$[0, 180]$	[1, 2, 25]
3	40	500	36, 52	assembly, general	1	1	$[50, 950]$	$[0.2, 4]$	$[0, 180]$	[25]

example in Table 1). In classes 2 and 3 the setup costs s_i for each item are randomly selected from a uniform distribution. The inventory holding costs h_i for each item are randomly chosen so as to guarantee that the average inventory holding costs per level decrease with increasing level code. A more detailed description of the instances can be found in Dellaert and Jeunet [25]. Solutions with minimum total costs are known for all instances for class 1, and 14 instances for class 2. For the remaining instances no optimal solutions are known.

The set $I = \{1, \dots, N\}$ of items is distributed to n ($n = 2, 5$) facilities to generate a multi-facility instance based on an MLULSP instance. The items are assigned to facilities $F_1, \dots, F_n$ as follows:

$$F_1 = \{1, \dots, NF_1\}, \tag{11}$$

$$F_n = \left\{\sum_{k=1}^{n-1} NF_k + 1, \dots, N\right\}. \tag{12}$$

The numbers NF_k, $k = 1, \dots, n$, of items per facility F_k were determined with the aim of generating multi-facility instances with a considerable conflict between the agent's objectives. Therefore the following steps were executed:

- Generate six multi-facility instances with different, randomly selected values for NF_k, $k = 1, \dots, n$, from each MLULSP instance.
- Solve each generated instances with different procedures (see Sect. 5.2). Since many potential solutions are generated, it would be possible to calculate the correlation coefficient $corr(C_1, C_2)$ between the local costs C_1 and C_2 of the facilities F_1 and F_2. Positive correlations would indicate that there is no real conflict between the local costs of the facilities or agents, negative correlations would indicate the presence of a conflict.
- Select the instances with the highest level of conflict, i.e. with the lowest correlation coefficient.

The number of selected instances (*NOI*), the average number of items per facility, and the average correlation coefficient are shown for each class in Table 5.

The generated multi-facility instances of class 1 show the highest level of conflict. This can be attributed to the values of the cost parameters (increasing setup costs and decreasing inventory holding costs along any branch of the product structure). All instances of class 1 are characterized by a non-cyclic decomposition. Most instances of classes 2 and 3 with $n = 5$ facilities are characterized by a cyclic decomposition. In

Table 5 Problem instances of the reformulated MLULSP

Class	$n=2$				$n=5$						
	NOI	NF_1	NF_2	*corr*	*NOI*	NF_1	NF_2	NF_3	NF_4	NF_5	*corr*
1	30	2.0	3.0	−0.51	30	1.0	1.0	1.0	1.0	1.0	−0.55
2	10	11.0	32.0	−0.13	10	2.4	4.7	7.7	10.7	17.5	−0.17
3	5	34.0	466.0	−0.01	10	1.7	41.5	76.4	131.0	249.4	−0.08

particular a cyclic decomposition motivates a simultaneous coordination of all agents and thus applying the proposed ES-CM (in case of a non-cyclic decomposition it is also possible to apply approaches where agents negotiate in pairs).

5.2 Implemented methods

The following decentral solution procedures were implemented:

- ES-CM: An agent-based procedure, where n agents are coordinated by the new ES-CM. $\lambda = 50$ was chosen in all runs. Each run of class 1 (class 2, class 3) was terminated after $maxr = 1000$ (4000, 8000) rounds, i.e. 50000 (200000, 400000) proposals were generated per run.
- SA-CM: An agent-based procedure, where n agents are coordinated by the mechanism by Fink [36–38]. The mechanism is based on the idea that, in each round, one contract proposal is generated by mutation of the current contract c. The agents votes for or against the acceptance of new proposals in accordance with a Metropolis acceptance criterion. The parameters of the mechanism (the acceptance ratios of the agents) were determined according to Fink [36, 37]. The implied objective in SA-CM is to find social efficient solutions [36], regarding our problem that means to minimize the total costs. Each run for an instance of class 1 (class 2, class 3) was terminated after 50000 (200000, 400000) generated proposals to reach a comparability with ES-CM.

According to the given problem decomposition into two or five facilities, multi-facility instances were solved with $n = 2$ or $n = 5$ agents.

In addition to the decentral approaches the following central approach was also implemented.

- PGA*: A simple modification of the parallel genetic algorithm (PGA) described in Homberger [44]. As opposed to the PGA, which minimizes the total costs, PGA* aims to minimize the local costs of the worst-off agent. Therefore, in comparison to ES-CM and SA-CM, the local costs of the agents are assumed to be public. Each run for an instance of class 1 (class 2, class 3) was terminated after 50000 (200000, 400000) generated proposals to reach a comparability with the decentral approaches.

All methods were implemented in Java. In accordance with the literature, all processes are executed and tested on a single computer [58]. Each calculation run was carried out on an AMD Athlon 64 3000 CPU (1 GB RAM) operating under Win XP SP2.

5.3 Comparison of results

In accordance to Dudek and Stadtler [29, 30] the quality of solutions obtained by the decentral approaches ES-CM and SA-CM are measured as the percentage gap to corresponding solutions obtained by the central approaches. Since fairness and social efficiency are possible objectives for coordination the following two gap measures are used:

$$GAP^{\text{fair}} = \frac{MC^{\text{dec}} - MC^{\text{cen}}}{MC^{\text{cen}}} \times 100, \tag{13}$$

Table 6 Average values of GAP^{fair}

Class	$n = 2$		$n = 5$	
	ES-CM	SA-CM	ES-CM	SA-CM
1	**5.2**	14.7	**7.9**	61.8
2	**2.3**	11.1	**19.6**	25.4
3	**1.6**	3.6	**10.2**	18.0

Table 7 Average values of GAP^{eff}

Class	$n = 2$		$n = 5$	
	ES-CM	SA-CM	ES-CM	SA-CM
1	8.2	**0.8**	18.0	**1.8**
2	11.4	**8.3**	44.9	**26.0**
3	31.2	**22.2**	110.9	**80.2**

$$GAP^{\mathrm{eff}} = \frac{TC^{\mathrm{dec}} - TC^{\mathrm{cen}}}{TC^{\mathrm{cen}}} \times 100. \tag{14}$$

GAP^{fair} and GAP^{eff} are computed using different reference solutions. In (13) MC^{cen} denotes the maximum local costs of a solution obtained by PGA*. That means, MC^{cen} is taken from a solution which maximizes the fairness criterion. It represents a lower bound for the maximum local costs. In (14) TC^{cen} denotes the total costs of the optimal or best known solution for the MLULSP published in the literature [25, 44, 71]. That means, TC^{cen} is taken from a solution which minimizes the total costs, i.e. a solution which maximizes the social efficiency. MC^{dec} and TC^{dec} denote the maximum local costs and the total costs of a solution obtained by a decentral approach (ES-CM or SA-CM). The average gap values of the decentral approaches are given in the Tables 6 and 7.

The following observations are made based on Tables 6 and 7:

- *Comparing the ES-CM with the SA-CM based on fairness or maximum local costs* (Table 6). The GAP^{fair} for a solution obtained by ES-CM is on average smaller than the gap value of corresponding solution obtained by SA-CM. The significance of results was checked by the Wilcoxon signed rank test [89] with a significance level of 1%. The results were significant for each class, i.e. the hypothesis that ES-CM and SA-CM yield the same gap values was rejected and the alternative hypothesis that SA-CM yields solutions with a higher gap to central solutions than ES-CM was accepted.
- *Comparing the ES-CM with the SA-CM based on the social efficiency or total costs* (Table 7). The GAP^{eff} value for a solution obtained by SA-CM is often smaller than the corresponding value of ES-CM. The significance of results was checked by the Wilcoxon signed rank test with a significance level of 1%. The results were significant for each class, i.e. the hypothesis that ES-CM and SA-CM yield the same gap values was rejected and the alternative hypothesis that ES-CM yields solutions with a higher gap to central solutions than SA-CM was accepted.

- *Comparing the ES-CM with the central approaches.* As expected, the solution quality of the decentral procedure ES-CM is lower than that of the central procedures. The gap values can be traced back to the autonomy of the planning agents and the assumed asymmetric information. The work of Dudek and Stadtler [29] should be mentioned for the evaluation of the gap values. The authors indicate an average decentral planning GAP^{eff} of 1.9% (calculated for instances of MLCLSP). It should be pointed out that Dudek and Stadtler [29] conduct a negotiation with $n = 2$ agents and only small problem instances with up to $N = 10$ items (compared with $N = 500$ items used here). Moreover, the approach of Dudek and Stadtler [29] aims to minimize the total costs.

According to Dudek [28] the results (across the test instances of class 1) are examined more closely in Fig. 6 which shows frequency distributions of the number of test instances as a function of the GAP^{fair} to central planning. The bars indicate for ES-CM gaps to central planning of less than 5% in 57% of the test instances with $n = 2$ facilities. Another 40% of test problems yield a gap of 5 to 15%, and 3% falls into the interval of 15 to 30%. This situation changes drastically for SA-CM where 36% of test problems yield a gap of 30 to 70%. For instances with $n = 5$ facilities the differences between both approaches become more significant. For ES-CM the

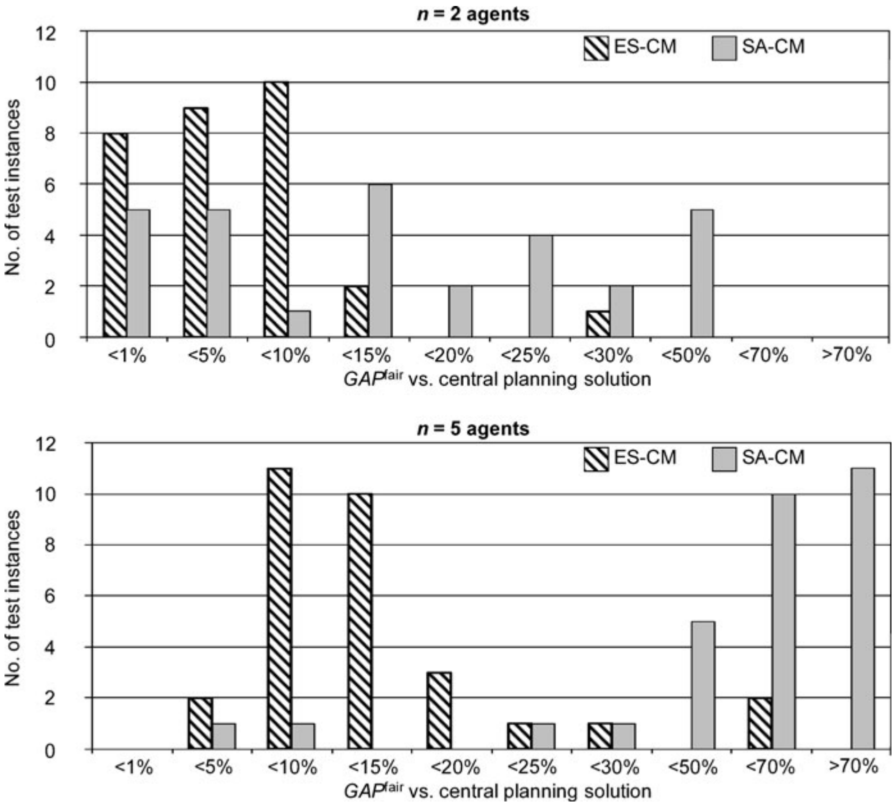


Fig. 6 Frequency distribution of gaps

Table 8 Average cost distribution

Class	*NOI*	Facility	Average local costs C_k of facility F_k		
			PGA*	ES-CM	SA-CM
1	30	F_1	457.88	461.11	479.39
		F_2	454.33	431.01	383.90
1	30	F_1	211.74	221.81	346.77
		F_2	189.99	155.23	110.82
		F_3	196.13	154.36	106.56
		F_4	185.03	151.90	118.56
		F_5	187.23	160.00	123.18
2	10	F_1	152420.06	143112.16	171991.19
		F_2	152853.82	144362.25	118264.48
2	10	F_1	98061.91	98114.75	121843.99
		F_2	98849.11	81974.33	51133.73
		F_3	93248.37	75218.40	58215.41
		F_4	90076.85	75467.75	42733.70
		F_5	72039.77	76101.46	51485.74
3	5	F_1	1791134.19	1919192.11	2414765.57
		F_2	2342742.34	2259363.02	1720659.06
3	10	F_1	3916094.06	3437557.34	2447039.15
		F_2	8683402.00	8122560.79	7726572.58
		F_3	7408045.87	7208145.77	8395454.35
		F_4	17095457.88	17664223.09	18884010.77
		F_5	9122276.03	8007409.05	1149373.26

majority of test results (more than 85%) have gaps to central planning of less than 30%. For SA-CM gaps to central planning between 30 and 100% are most frequent.

To analyze the computed cost distributions, the average local costs C_k for the different facilities F_k, $k = 1, \dots, n$, computed by PGA*, ES-CM, and SA-CM, are given in Table 8. The table shows that the central method PGA* computes solutions in which the total costs between the agents are more balanced than in solutions obtained by the decentral approaches. This was expected, since PGA* minimizes the local costs of the worst-off agent directly. Moreover, from Table 8 it can be observed that the average total costs are more balanced in the solutions obtained by ES-CM compared to the corresponding solutions obtained by SA-CM. This is due to the fact, that SA-CM maximizes the social efficiency and not the fairness criterion.

As shown in Table 8 the average result from ES-CM dominates the average result from PGA* for class 2 and $n = 2$ facilities. However, a comparison of solutions obtained by ES-CM, SA-CM, and PGA* for the individual instances shows, that none of the three methods dominates another method in any particular instance, i.e. it leads to a lower costs for all agents.

5.4 Analysis of the coordination mechanism ES-CM

The impact of the parameter λ on the solution quality is analyzed for the instances of class 1 with a decomposition in $n = 2$ facilities. Table 9 shows the average gap value GAP^{fair} in dependence of the parameter λ. The total number $\lambda \times maxr$ of generated proposals was set to 50000 in each run.

As can be seen from Table 9 the selective pressure $1/\lambda$ has a considerable impact on the solution quality. For $\lambda < 50$ often solutions with higher maximum local costs were computed. These results were checked by using the Wilcoxon signed rank test with a significance level of 1%. For example, the differences on maximum local costs of the solutions were significant, being computed either with $\lambda = 25$ or with $\lambda = 50$. Since the Borda maximin rule violates the axiom of independence of irrelevant alternatives it was interesting to see that $\lambda = 50000$ leads to worse solutions in comparison to $\lambda = 50$. In this case all proposals were generated simultaneously at the beginning of the coordination and the agents vote only once. The significance of these results was also checked by using the Wilcoxon signed rank test with a significance level of 1%.

To analyze the convergence of ES-CM the average solution quality over all instances of class 2 (parameter values for ES-CM: $maxr = 4000$, $\lambda = 50$) with $n = 2$ facilities for the accepted contract c after 0, 1000, 2000, 3000, and 4000 rounds are given in Table 10.

Table 10 shows that ES-CM produces jointly improving solutions or joint gains with an increasing number of rounds. In the following the convergence for ES-CM is discussed in detail, taking one selected instance of class 2 as an example. Figure 7 shows the maximum local costs in monetary units (MU) of the accepted contract c for each round.

The Pareto optimality of solutions should be also discussed. Figure 8 shows the local costs of the accepted contract c for each agent, plotted next to the Pareto efficient line. This line was estimated by applying PGA to different weighted sums of the two

Table 9 Impact of parameter λ on the solution quality

λ	1	25	50	100	500	2000	50000
$maxr$	50000	2000	1000	500	100	25	1
GAP^{fair}	21.7	11.3	6.6	7.1	7.9	9.2	33.8

Table 10 Average cost values for the generated multi-facility instances of class 2 ($n = 2$)

Number of rounds	Total costs TC	Maximum local costs MC	Local costs C_1	Local costs C_2
0	787727.59	444762.92	443191.84	344535.75
1000	302795.41	165033.54	149522.85	153272.56
2000	291274.98	152125.02	144137.61	147137.37
3000	288926.31	150221.76	143632.80	145293.51
4000	287474.41	149706.10	143112.16	144362.25

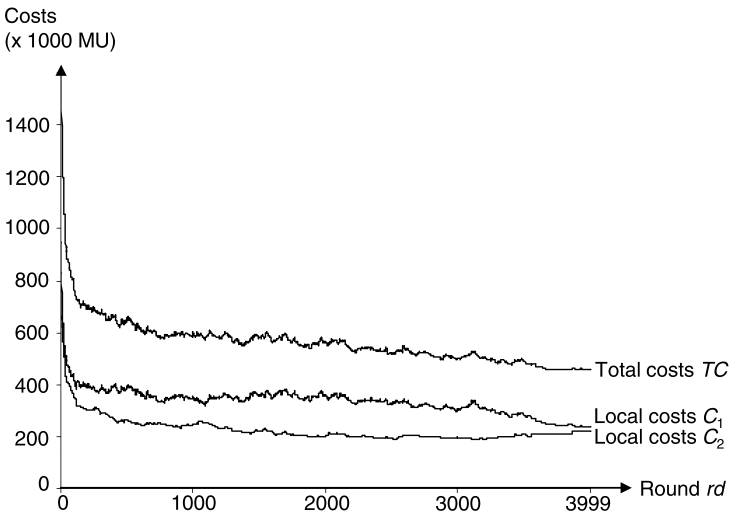
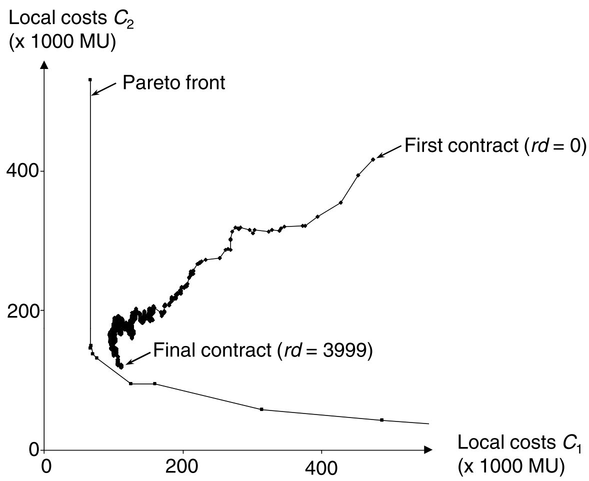


Fig. 7 Convergence of ES-CM for an instance of class 2

Fig. 8 A typical coordination with two agents for an instance of class 2



agents' cost functions [53]. As can be seen from Fig. 8, the agents search a wide range of possible contracts, ending very near to the Pareto front.

6 Discussion and future work

A new mediator-based mechanism (ES-CM) to coordinate n self-interested agents who are searching for an agreeable contract of multiple interdependent decision variables is presented. The approach takes given asymmetric information into account. The mechanism uses an evolution strategy at the aggregate (group) level to generate multiple contract proposals in each round upon which the individual group members vote. The intention of this voting is to determine compromise search directions. Since the approach is generic with regard to the kind of contract under consideration, it can be applied to many coordination problems. In order to test the potential of the new mechanism to compute efficient and fair solutions for a decentral production planning scenario the MLULSP is reformulated as a group decision problem. Moreover, the CM by Fink [36, 37], denoted as SA-CM, was also implemented for the reformulated problem. To compare both approaches 95 problem instances of the reformulated problem were generated on the basis of published instances of the MLULSP. The results show that ES-CM was able to find fairer solutions than SA-CM.

In the following the contribution of this paper in relation to prior works is described and some recommendations for future work are also given.

Most prior works on the MLULSP, including those by the author himself [44, 45], are based on the assumption of an existing central decision authority, i.e. one unit who has the power to make decisions for all items and who aims to minimize the total inventory and holding costs. Moreover, these works assume that all planning information is centralized. In this paper these assumptions are removed. Thus, the main contribution of this paper to most prior work on the MLULSP is that it presents two decentral approaches (ES-CM and SA-CM) which address the complications that arise from decentralized decision making. The work by Lee and Kumara [59] has the same intention. The authors use the MLULSP to model a SC which consists of one supplier and multiple buyers. However, the model of Lee and Kumara [59] differs from the model used in this paper. Firstly, Lee and Kumara [59] use only a two-level version of the MLULSP. Within the decomposition each item is assigned to a different facility. Secondly, Lee and Kumara [59] assume that the supplier is willing to reveal its inventory holding costs. Thus, the main contribution of this paper in relation to the work of Lee and Kumara [59] is that it also considers general product structures (and thus structures with more than two levels) and a higher level of information asymmetry.

ES-CM appears superficially similar to the method described by Homberger [44], a parallel genetic algorithm (PGA) for the MLULSP. Both approaches are based on the same representation of solutions and use the same mutation operator. Moreover, the two approaches consist of several search processes which cooperate with each other during the search and which can be executed in parallel on several computers. This similarity motivates a detailed distinction between the two approaches. Firstly, each search process in PGA executes a genetic algorithm to generate solutions for the MLULSP. Thus, multiple search paths are executed concurrently. In comparison to this, each search process in ES-CM represents an agent who evaluates solutions proposed by the mediator on the basis of a private objective function. Since solutions are only generated by the mediator, one search path in the solution or contract space is executed by ES-CM. Secondly, each search process in PGA has all planning information and is guided by the objective to minimize the sum of setup and inventory costs of all items according to (1). Each agent in ES-CM wants to minimize its local costs according to (8). Thirdly, process cooperation in PGA is achieved by the exchange of solutions between the search processes and is motivated by speeding up the execution time. Process cooperation in ES-CM is achieved by accepting non-deteriorating proposals during the search to compute win–win opportunities. Fourthly, PGA uses a binary tournament selection meanwhile the selection procedure in ES-CM combines the selection procedure of evolution strategies, a time-decreasing acceptance probability for inferior solutions and the Borda maximin voting rule.

ES-CM uses effective ideas from prior works on mediator-based approaches, namely the determination of compromise search directions [32] and the acceptance of deteriorating proposals by a time-decreasing probability [52, 53]. This motivates an attempt to elaborate the differences between these works and to clearly identify the contribution of this paper in relation to the previous works.

- There are two essential differences between ES-CM and the negotiation approach by Ehtamo et al. [32]. Firstly, the approach of Ehtamo et al. [32] assumes a negotiation problem which covers continuous decision variables. This approach is not applicable for problems with non-continuous decision variables, e.g. the reformulated MLULSP. Since the decision variables are continuous the mediator can apply a gradient search procedure to generate compromise proposals by means of the preferences of the agents. Secondly, the approaches differ with regard to the acceptance of proposals. In Ehtamo et al. [32] only superior proposals are accepted. Thus, as shown by Klein et al. [52], the search process may get stuck rather soon. ES-CM avoids this risk by letting the mediator also accept inferior proposals given a time-decreasing probability. Thus, two contributions of this paper towards the previous works by Ehtamo et al. [32] are identified: (1) This paper shows a way to determine compromise search directions in case of non-continuous decision variables. (2) This paper shows a way to avoid an early stagnation of the search process.
- There are two essential differences between ES-CM and the negotiation approach by Klein et al. [52, 53]. Firstly, the approach by Klein et al. [52, 53] generates one proposal per round. Secondly, the acceptance of an inferior proposal is computed by means of the Metropolis probability, which requires that the agents reveal more information (not only preferences) to enable the mediator to roughly assess the quality of generated proposals. Klein et al. [52] suggested that the agents classify votes as strong or weak. As mentioned by Fink [36] it is not quite clear how the agents should achieve a suitable classification. Thus, the contribution of this paper towards the previous works by Klein et al. [52] is that it shows an alternative way to use a time-decreasing probability without the problematic classification of votes.

The approaches by Ehtamo et al. [32] and Klein et al. [52] have been tested only for a few small and not published problem instances. Thus, another contribution of this paper towards these prior works is to provide a benchmark for coordination approaches which is based on many large and published problem instances.

Two opportunities for further research work are mentioned here. First, instead of the Borda maximin rule other voting rules could be tested within ES-CM. Since the Borda maximin rule violates the axiom of independence of irrelevant alternatives, it is motivated to use and test other voting rules which satisfy this axiom. Second, the suggested coordination mechanism ES-CM has to be validated for more realistic planning problems or SC settings, e.g. for decentral variants of the MLCLSP [28] and for the simultaneous lot-sizing and scheduling problem [35].

Acknowledgements The author would like to thank three anonymous reviewers and the anonymous assistant editor for their helpful comments. One of the reviewers gave especially detailed comments for which I'm especially grateful. Special thanks are also due to Philipp Schulte-Hubbert and Julian Elsäßer for supporting the implementation.

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