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# A robust decentralized decision-making approach for mobile supply chains under uncertainty

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## ABSTRACT

The mobile supply chain (MSC) is a new concept that allows companies more adaptability and flexibility. In MSCs, a product family can be produced, distributed, and delivered by a mobile factory, carried by trucks, and shared among different customers. In this paper, to optimize production scheduling and the mobile factory routing problem under uncertainty, a robust decentralized decision-making approach (RDDMA) based on the Analytical Target Cascading (ATC) approach is developed. The RDDMA is a bi-level hierarchical optimization method that divides an all-in-one model into sub-problems and aims to address each agent's target. It is a 4-phase procedure, including time window determination, robust mobile factory routing, actual production scheduling, and adjustment. In real-world applications, the service time at each site is uncertain. Therefore, a scenario-based robust optimization approach is utilized to manage the uncertainties of the problem. Finally, the RDDMA performance is evaluated using several instances. The results suggest the proposed approach can provide robust solutions for such a multi-agent problem.

**KEYWORDS:** Decentralized decision-making · Analytical Target Cascading · Robust optimization · Mobile supply chains · Shared factory.

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## 1. INTRODUCTION

The mobile supply chain (MSC) concept has its origins in the Distributed Manufacturing System (DMS) concept, which tries to produce a product family locally. In MSCs, a truck can carry the so-called mobile factory (MF) to provide on-site service for geographically dispersed customers [1]. One of the main advantages of this concept is the opportunity to share (rent) expensive assets (machines), because these machines have a low or temporary usage rate at manufacturing sites (MS), and they are not needed continuously.

The idea of a Shared Factory is built on the concept of the sharing economy [2] and social manufacturing [3], which aims to share manufacturing resources and capabilities [4]. These concepts enable people to share services and facilities in a coordinated Peer-to-Peer (P2P) method. The best examples of this concept are Uber in transportation and Airbnb in the hotel industry. It can be expected that sharing resources (e.g., production machines) will lead to more sustainable and productive supply chains [5].

Applications of the shared factory and mobile supply chains can be found in various business sectors, from humanitarian logistics to modular production units. For example, blood from donors in remote areas can be collected by mobile blood donation units [6]. Furthermore, mobile clinics [7] and laboratories are utilized to deliver medical services and urgent services in remote areas. Customers' orders can be printed using a shared 3D printing factory which can be moved via a truck to the required location [8]. Finally, in chemical industries, production machines (e.g., reactors) can be carried in moveable containers by truck. A few grams for very early research to hundreds of tons for mass-produced goods [9] can be provided by mobile modular production units locally.

The MSC is inherently a complex multi-agent decentralized problem. The production processes at MSs cannot be completed if an MF is not available there. On the one hand, the mobile factory service provider (MFSP) aim to minimize transportation and operating costs. On the other hand, production managers at MSs try to deliver their own customers' job orders in time. In many cases, these agents' goals can be in conflict, where the fleet manager cannot meet the production managers' demanded service in time.

In this paper, a robust decentralized decision-making approach is proposed for MSCs under uncertainty. In order to implement decentralization, an ATC is utilized, which decomposes a centralized model into sub-problems. Accordingly, the MF's fleet manager is chosen as the upper level agent, and production managers are considered as lower level agents. Furthermore, since service times at MSs are uncertain, three uncertainty scenarios are developed to address optimistic, realistic, and pessimistic scenarios of data realization. Finally, a scenario-based robust optimization approach is used to tackle the problem uncertainties by reformulating a robust facility routing problem. Using the proposed concept, all agents can reap the benefits of decentralization, robustness, and service flexibility provided by MFs. In this paper, some gaps in the mobile supply chain scope are fulfilled, with contributions as follows:

- Presentation of a robust optimization model in the field of the shared/mobile factory.
- Proposal of a coordinated method for MSCs which takes into account the MF routing and production scheduling problem.
- Suggestion of a decentralized decision-making approach for MSCs based on ATC.
- Contrary to simple production routing problems, the production process is performed at the customer's location instead of the depot point.

The remainder of this paper is organized as follows. Section 2 briefly reviews related works and efforts and Section 3 explains the problem and discusses the basis of the ideas proposed in this paper. In Section 4, the decentralized decision-making approach and mathematical models are described and, in Section 5, data generation and numerical results are presented. A conclusion and recommendations for future research are described in Section 6.

## 2. LITERATURE REVIEW

To the best of our knowledge, the idea of the MF was presented first under the name Factory-in-a-Box [10]. However, similar ideas have developed following this concept which are more or less different names for the same concept. For example, plug and produce [11], mobile on-site factory [12], location-independent [13], and movable production systems [14]. These are simply different names for the same concept.

Based on two well-known concepts, namely the sharing economy [15] and collaborative consumption [16], the shared factory idea was introduced by [4]. Accordingly, manufacturers can share their manufacturing resources without limitation. Similarly, shared manufacturing was introduced by [17], whereby they referred to it as SharedMfg. In their research, the concept, definitions, and operation services of SharedMfg were investigated and compared with similar ideas.The shared factory performance was studied from sustainability and efficiency points of view [8]. In that paper, they proved shared factories enhance resource productivity and manufacturing sustainability. For this purpose, a 3D-printing mobile prototype was used.

Some variants in the vehicle routing problem (VRP) are similar to the MSC. Nevertheless, these variants do not cover all aspects of the problem. The main focus in VRP is the routing part of the problem and ignores the other interconnected sections in the supply chain. In the MSC, the production scheduling problem at MSs plays an important role in finding a feasible and optimal solution.

The mobile facility routing problem [18] has the most similarity with the MSC concept among variants of VRP, which aims to optimize routes for a fleet of mobile facilities. Lei et al. [19] proposed a two-stage stochastic optimization model for a mobile facility routing problem. The first stage decision considers the temporal movement of mobile facilities, and the second stage addresses mobile facility service at the manufacturer's site. The model was solved using an algorithm based on the L-shaped method. A mathematical model was recently proposed for the Factory-in-a-Box routing problem. The proposed model was solved using an exact solver and metaheuristics algorithms for large-scale instances [20]. Finally, a centralized multi-objective mixed-integer mathematical model was proposed to address the MSC problem with mobile factories. The objective function minimizes transportation costs and delay costs considering the coordination of the mobile factory movements and production plan at manufacturing sites [21].

The production routing problem [22] and vehicle routing problem with service time [23] are other variants of the VRP which are similar to the MSC concept. However, in these problems, the production process is performed at starting points (depots), while in the MSCs each customer has a production line that depends on the mobile factory to start, continue, and complete the process. Nevertheless, in the production routing problem, the integration of production, location, inventory, and distribution problems [24]; the integration of a supply chain considering production, inventory, and routing decisions [25]; and the integration of disassembly line balancing and routing problems [26] have been studied recently.

Decentralized decision-making approaches in the supply chain have been investigated widely. Some of the most well-known methods to apply decentralization on optimization models in supply chain are as follows:

multi-level optimization [27], game theory [28], and ATC [29]. Furthermore, some authors present heuristic methods which are designed for a particular context [30]. To solve the resulting decentralized models, the KKT conditions, kth-best, or metaheuristic algorithms are used to solve bi-level models [31].

## 3. PROBLEM STATEMENT AND THEORETICAL BACKGROUND

This section describes the problem, illustrates the application of the MF, and introduces the methodologies used in this paper. For this purpose, we first explain the mobile factory and mobile supply chain structure and components. After that, the ATC method and its procedure and the scenario-based robust optimization method are described.

The studied problem in this paper is inspired by a real-world application in the chemical industry. As illustrated in Fig. 1, some critical production equipment (e.g., reactor) are embedded in an MF. The MF can be carried by truck to produce a product family whenever and wherever required. It can produce different intermediate products which can be used in various manufacturing steps in the semiconductor industry or similar industries.

Because of the relatively low production rate, this expensive and high-tech equipment is not needed at production sites all the time. Hence, sharing this equipment would be a wise decision by the main supplier of the products. The supplier company (MF owner), which is a chemical company, can control the MF production remotely via controllers. Using this idea, the supplier can enhance its service level, minimize production costs, know-how leakage, and avoid extra transportation costs.

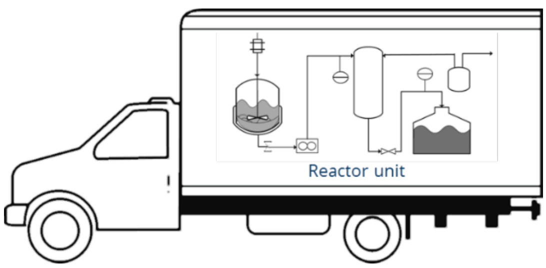


*Fig. 1: Schematic of a mobile factory*

The MS has a flow shop production line with several production machines in a row, where the shared production machine (SPM) can be located at any step of production. When the MF is available at a MS, the production process at a pre-determined SPM can start, continue, and complete. In other words, the MF is a temporary production resource at the MS. Therefore, MSs (as the lower level agents, i.e. followers) and the MFSP (as an upper level agent, i.e. leader) should work in a coordinated manner. Otherwise, the MF would be available at the MS, and all job orders would be delayed because it is too late, or there would be no job order to process because it is too early.

The configuration of decision making in a supply chain can be in a centralized or decentralized way. The agents introduced in this problem have conflicting goals, which makes the stated problem intrinsically decentralized. Utilization of a decentralized decision making approach not only decreases the problem complexity but also takes into account information security and agent autonomy. Therefore, the decentralized decision-making approach fits better with this problem.

### 3.1. ATC

ATC has at least two levels, and an optimization problem exists for each level. Accordingly, coupling variables connect these optimization problems hierarchically, and it should be noted there is no link between optimization models from the same level. Although the coupling variables are called target variables from the upper level perspective, they are response variables from the lower level view. Values of the target variables are determined by the upper level and distributed down to the lower levels. Then, the lower levels check how close they are to their targets. According to a penalty cost function, the upper level can revise its decision to help the lower levels reach their targets [32].

As it was proven, bi-level models are NP-hard [33]. One of the most common approaches to solving these models is the Karush–Kuhn–Tucker (KKT) condition, which is based on reformulating an equivalent single-level model [34]. Since classic bi-level optimization methods increase the problem complexity, evolutionary algorithms are used to handle this shortcoming [35]. Contrarily, ATC decreases the problem complexity by decomposing the problem into several smaller sub-problems.

A simple hierarchical model for the MSC is demonstrated in Fig. 2 to explain the ATC procedure generally. An all-in-one routing production problem is reshaped to a bi-level problem. The MFSP represents the upper level, which manages a couple of MFs and indicates their presence period at MSs, while the lower level contains production scheduling units at different MSs. Firstly, they propose their desired time window (TW) for the MF presence period based on their job orders' due dates. The upper level collects all TW proposals from the MSs and evaluates its transportation and operation costs accordingly. Then, the upper level determines the period that they will be available at each MS. After receiving the response variable answer from the upper level (MF presence period), the lower level checks to what extent they can complete their orders in time. If it is far from their desired TW and induces too many delayed orders, they have to negotiate with the upper level to revise their plan.

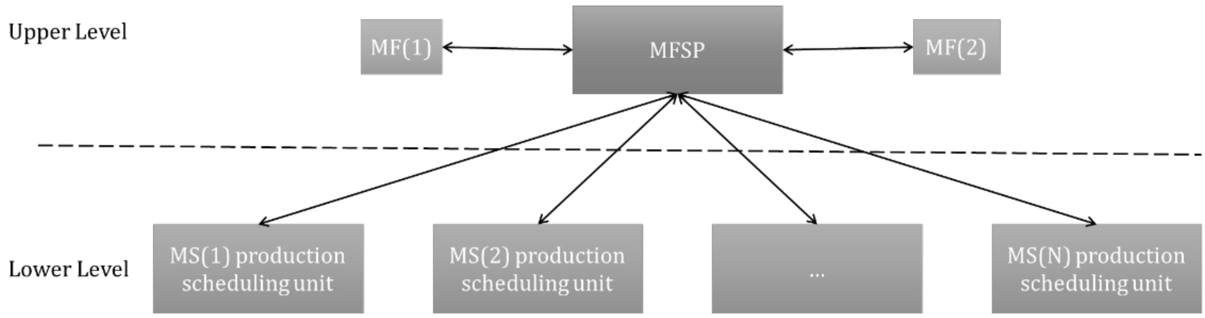


*Fig. 2: The MSC hierarchal structure*

### 3.2. Scenario-based robust optimization method

In scenario-based robust optimization methods, some uncertainty scenarios $s \in S$ are defined for the uncertain parameter, which represents the parameter values under different circumstances. Based on the method proposed by [36], constraints and variables are categorized into two major groups: structural and control. Structural variables remain unchanged in all probable scenarios, while control variables are adjusted whenever the uncertain parameter is realized [37]. For example, consider the following uncertain model:

$$Min\ Z = c^T x + d^T y \tag{1}$$

*Subject to*:

$$Ax = b \tag{2}$$

$$Bx + Cy = e \tag{3}$$

$$x, y \geq 0 \tag{4}$$

Where $x$ and $y$ are structural and control variables, respectively. Constraints (2) and (3) represent structural and control constraints. To reformulate the uncertain model robust counterpart, a set of scenarios $S = \{1,2,3, \ldots, S\}$ with the probability $p_s (\sum_{s=1}^{S} p_s = 1)$ is defined. Moreover, $\{\delta_1, \delta_2, \ldots, \delta_s\}$ is the set of error vectors and constraint (4) defines the domains of the decision variables. The linear robust counterpart for the abovementioned model is as follows:

Where objective function (5) has three terms that aim to minimize the expected value of the objective function, variance of the objective function, and infeasibility costs. Constraint (6) was proposed by [38] to linearize using an auxiliary variable ( $\theta_s$ ) the robust counterpart presented by [36]. Finally, constraint (8) is the reformulation of control constraint (3), and constraint (9) defines the domains of the decision variables.

## 4. MATHEMATICAL FORMULATION

In this section, several mathematical models for the MSC routing production problem are developed. As explained in Section 3, to reformulate the decentralized decision-making approach, at least two levels exist, and each level has its own corresponding mathematical model. Therefore, the mathematical models and decision-making approaches are proposed in the following.

There is a set of job orders ( $n \in N$ ) with a due date of $du_n$ which are processed via a flow shop production line with $m \in M$ production machines. Only when an MF is present at the MS the production process on a pre-defined SPM can be started, continued, and finished. Hence, production planners at MSs should take into account the MF presence time ( $Z_i$ ) and align

$$Min\ Z = \sum_{s \in S} p_s \xi_s + \lambda \sum_{s \in S} p_s [(\xi_s - \sum_{s' \in S} p_{s'} \xi_{s'}) + 2\theta_s] + \omega \sum_{s \in S} p_s \delta_s \tag{5}$$

*Subject to*:

$$\xi_s - \sum_{s' \in S} p_{s'} \xi_{s'} + \theta_s \geq 0 \qquad \forall s \in S \tag{6}$$

$$Ax = b \tag{7}$$

$$B_s x + C_s y_s + \delta_s = e_s \qquad \forall s \in S \tag{8}$$

$$x \geq 0, y_s \geq 0\ \ \theta_s \geq 0 \qquad \forall s \in S \tag{9}$$

with the operation start time on SPM ($ST_{SPM}$). Finally, decision variables should be determined in such a way that minimizes the total delayed job orders ($DL_n$).

To optimize the MF routing problem, three main cost drivers should be considered. Although transportation costs are computed according to traveled distance, operation costs (e.g., crew costs) are calculated based on each MF's tour duration. On the other hand, delay costs refer to the TW violation penalty. The TW proposed by each MS can be violated by paying a cost rate $\delta$ . It should be mentioned that each MS has raw material demand size $q_i$ and the capacity of the MF is restricted ($dc$).

Modeling indices, parameters, and decision variables are defined below.

*Sets*

| | |
|---|---|
| $I$ | Customer MSs, where $i, j \in I$ |
| $N_i$ | Job order at MS $i \in I$ , where $n \in N_i$ |
| $M_i$ | Machines at MS $i \in I$ , where $m, l \in M_i$ |
| $K_i$ | Positions in sequence at MS $i \in I$, where $k, b \in K_i$ |
| S | Scenarios, where $\forall s \in$ S |

*Parameters*

| | |
|---|---|
| $p_{nm}$ | Processing time of job $n \in N$ on the machine $m \in M_i$ at MS $i \in I$ |
| $q_i$ | Demand of MS $i \in I$ |
| $dc$ | Capacity of MF |
| $di_{ij}$ | Distance between site $i$ and $j \in I$ |
| $\beta$ | Average transportation cost rate of MF, €/Km |
| $\alpha$ | Average operating cost rate for the MF, €/h |
| $\bar{v}_{ij}$ | Average speed of the MF to cross arc $(i,j)$ $i, j \in I$ |
| $du_n$ | Due date of job order $n \in N_i$ at MS $i \in I$ |
| $\omega$ | Delay cost €/h from MFSP point of view |
| $SE_i$ | MF service time duration at MS $i \in I$ |
| $h$ | Number of available MFs |
| $\mu$ | TW violation penalty, €/h |
| $\sigma$ | Delay cost (€/h) from manufacturer point of view |
| $p_s$ | Occurrence probability of each scenario $s \in$ S |
| M | A big number |
| $\lambda$ | Weight of the objective function variance |
| $dm_i$ | Demand of MS $i \in I$ |

*Variables*

| | |
|---|---|
| $X_{nk}$ | A binary variable equals 1 if job $n \in N$ is assigned to the sequence $k \in K_i$ at MS $i \in I$ ; 0, otherwise |
| $Y_{ij}$ | A binary variable equals 1 if arc $(i,j)$ $i, j \in I$ appears in the solution; 0, otherwise. |
| $T_{is}$ | Tour time duration of an MF which meets MS $i \in I$ as the last customer in the tour in each scenario $s \in$ S |
| $C_{km}$ | Completion time of kth job sequence on the machine $m \in M_i$ at MS $i \in I$ |
| $ST_m$ | Start time of service on machine $m \in M$ at MS $i \in I$ |
| $F_{ij}$ | Total amount of flow in arc $(i,j)$ $i, j \in I$ |
| $Z_{is}$ | Arrival time of the MF at site $i \in I$ in each scenario $s \in$ S |
| $DL_n$ | Delay time (hour) for job order $n \in N_i$ at MS $i \in I$ |
| $U_{is}$ | TW's upper-bound violation at MS $i \in I$ and each scenario $s \in$ S |
| $\xi_s$ | Objective function value in each scenario $s \in$ S |
| ES | Earliest time to start operation on SPM |
| LS | Latest time to start operation on SPM |

The problem assumptions are as follows:

- The MF fleet is homogenous.
- The MF can produce a product family.
- The MF has a fixed capacity.
- Each MS has a fixed demand.
- The MSs are homogenous.
- The SPM can be located on any step of the production line.
- The number of job orders at each MS can be different
- A penalty cost is determined on due date violation.
- The production line type is flow shop.
- To start, continue, and finish operation on SPMs, the presence of an MF is necessary.
- Each MF's tour starts from and ends at the depot node.
- Operation on SPM at MS has no stop (waiting) between two consecutive orders. Hence, $SE_i$ is equal with $\sum_{n=1}^{N_i} p_{nm}$, where m=SPM.
- MF service time duration at MS $i \in I$ ($SE_i$) is the uncertain parameter whose value can change in each individual scenario $s \epsilon$S.

### 4.1. Robust decentralized decision-making approach (RDDMA)

Now the RDDMA is presented based on the ATC method and the scenario-based robust optimization approach. This approach is designed based on decentralizing the MSC routing production problem under uncertainty. The decision-making approach is utilized to create a link between lower and upper levels efficiently. The overall 4-phase procedure is demonstrated in Fig. 3, and each phase explained as follows.

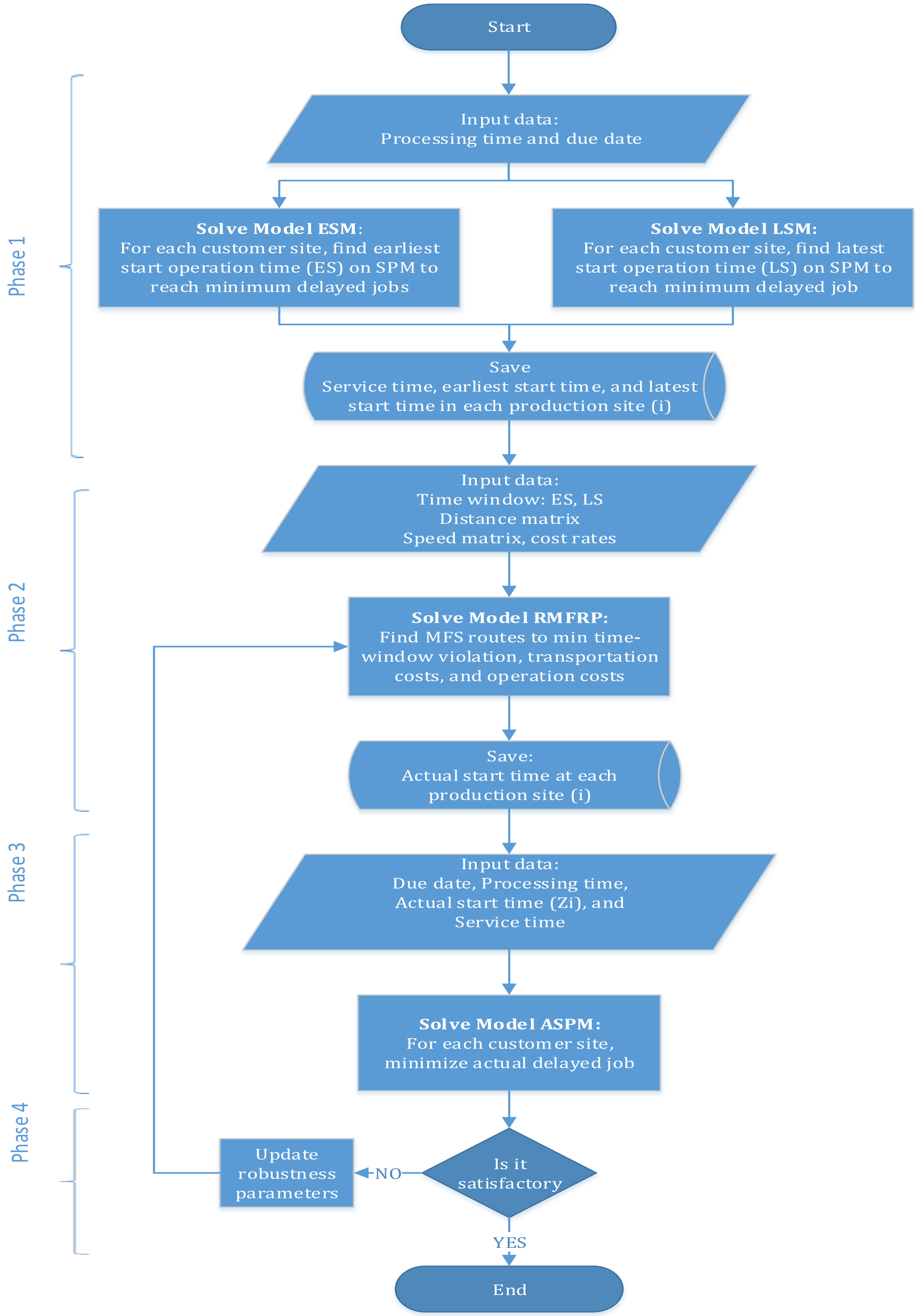


*Fig. 3: The proposed decentralized decision-making approach*

#### *4.1.1. Phase 1: Time window determination*

In this phase, each MS should propose its desired TW to reach minimum delayed orders. For this purpose, each MS should calculate the earliest (ES) and latest time to start (LS) operation on the SPM. Then, they inform the MFSP of their preferred TW. They perform orders with a minimum delay if an MF shows up at the MS in the proposed TW. Otherwise, they cannot meet their targets entirely. Hence, two mathematical models are required, namely the earliest start time (ESM) and latest start time (LSM) models, to calculate the TW information. These models are solved for each MS in parallel and the results are collected by the MFSP. Although in ESM the start time on SPM is minimized, it should be maximized in LSM. It is worth mentioning that these models are solved locally by each MS. Therefore, some sets (e.g. $N_i$ ) depend on index $i$, which addresses the MS(i). Finally, in both models the minimum delay is the main term in the objective function.

ESM:

$$Min\ Z = \sum_{n=1}^{N_i} \sigma DL_n + ES \tag{10}$$

Subject to:

$$\sum_{k=1}^{K_i} X_{nk} = 1 \qquad \forall n \in N_i \tag{11}$$

$$\sum_{n=1}^{N_i} X_{nk} = 1 \qquad \forall\, k \in K_i \tag{12}$$

$$C_{1m} \geq \sum_{l=1}^{l\leq m} p_{nl}\, X_{n1} \qquad \forall m \in M_i, n\ \in N_i \tag{13}$$

$$C_{1m} \geq C_{1,m-1} + p_{nm} X_{n1} \qquad \forall m > 1 \in M_i, n\ \in N_i \tag{14}$$

$$C_{k1} \geq \sum_{b=1}^{b\leq k} p_{n1} X_{nb} \qquad \forall\, k\ \in K_i \tag{15}$$

$$C_{km} \geq C_{k-1,m} + p_{nm} X_{nk} \qquad \forall\, k\ > 1 \in K_i, m \in M_i \tag{16}$$

$$C_{km} \geq C_{k,m-1} + p_{nm} X_{nk} \qquad \forall\, k\ \in K_i, m > 1 \in M_i \tag{17}$$

$$SE = C_{km} - ES \qquad \forall\, m = SPM \in M_i\,, \forall\, k\ \in K_i \tag{18}$$

$$ES = C_{1m} - \sum_{n=1}^{N} p_{nm}\, X_{n1} \qquad \forall\, m = SPM \in M_i \tag{19}$$

$$M(1 - X_{nk}) + du_n X_{nk} - C_{km} + DL_n \geq 0 \qquad \forall\, k \in K_i, n \in N_i, and\ m = |M_i| \tag{20}$$

$$X_{kn}\ \in \{0,1\}\,, C_{km}, ES, \text{and } DL_n \geq 0 \tag{21}$$

The objective function (10) minimizes delay and ES, while $\sigma$ adds more weight to reduce the delay term in the objective function. Constraints (11) & (12) ensure that each job is assigned to only one sequence and more than one job order is not given to each sequence, respectively. The processing times of the job orders and their completion time are calculated in constraints (13)-(17). Constraint (18) ensures that operation on SPM has no stop (waiting) between two consecutive orders. Constraint (19) computes ES, constraint (20) calculates the delay value, and constraint (21) defines the domains of the decision variables.

LSM:

$$Min\ Z = \sum_{n=1}^{N} \sigma DL_n - LS \tag{22}$$

Subject to (11)-(17), (20)-(21), and:

$$SE = C_{km} - LS \qquad \forall\ m = SPM \in M_i\ , \forall\ k\ \in K_i \tag{23}$$

$$LS = C_{1m} - \sum_{n=1}^{N} p_{nm} X_{n1} \qquad \forall\ m = SPM \in M_i \tag{24}$$

Where (22) is the objective function that minimizes delay while maximizing LS and constraints (23)-(24) compute the latest start time.

#### *4.1.2. Phase 2: Robust mobile factory routing (RMFR)*

Now the RMFR problem is formulated, which is a capacitated time-windowed vehicle routing problem with service time. Considering the initial information for the TW from the MSs, the fleet manager should trade off between time window violation, transportation, and operating costs. The RMFR problem is formulated as follows:

$$Min\ Z = \sum_{s\epsilon S} p_s\, \xi_s + \lambda \sum_{s\epsilon S} p_s[(\xi_s - \sum_{s'\epsilon S} p_{s'}\xi_{s'}) + 2\theta_s] + \omega \sum_{s\epsilon S} \sum_{i\in I} p_s U_{is} \tag{25}$$

Subject to:

$$\xi_s - \sum_{s'\epsilon S} p_{s'}\xi_{s'} + \theta_s \geq 0 \qquad \forall\ s\epsilon S \tag{26}$$

$$\xi_s = \sum_{i=1}^{I} \sum_{j=1}^{J} \beta di_{ij} Y_{ij} + \sum_{i=2}^{I} \alpha T_{is} \qquad \forall\ s\epsilon S \tag{27}$$

$$\sum_{i=1}^{I} Y_{ij} = 1 \qquad \forall\ j \in I \tag{28}$$

$$\sum_{j=1}^{I} Y_{ij} = 1 \qquad \forall\ i\ \in I \tag{29}$$

$$\sum_{j=1}^{I} Y_{0j} \leq h \tag{30}$$

$$\sum_{j=1}^{I} F_{ji} - \sum_{j=1}^{I} F_{ij} = dm_i \qquad \forall\ i\ \in I \tag{31}$$

$$F_{ij} \leq (dc - dm_i) \times Y_{ij} \qquad \forall\ i,j\ \in I \tag{32}$$

$$F_{ij} \geq dm_j \times Y_{ij} \qquad \forall\ i,j\ \in I \tag{33}$$

$$Z_{is} - Z_{js} + SE_{is} + \frac{di_{ij}Y_{ij}}{\bar{v}_{ij}} \leq M(1 - Y_{ij}) \qquad \forall\ i,j\ \in I, i \neq j, and\ j > 0, s\epsilon S \tag{34}$$

$$Y_{i1}Z_{is} + SE_{is}Y_{i1} + \frac{di_{i1}Y_{i1}}{\bar{v}_{i1}} = T_{is} \qquad \forall\ i\ \in I \tag{35}$$

$$ES_i \leq Z_{is} \leq LS_i + U_{is} \qquad \forall\ i\ \in I \tag{36}$$

$$Y_{ij} \in \{0,1\}\ , T_{is}, ST_{mi}, F_{ij}\ , Z_{is}\ , U_{is}, \text{ and } DL_{ni} \geq 0 \tag{37}$$

Where the objective function (25) expected MF costs and TW violation. Constraints (28) and (29) enforce that each MS should be visited only once, and constraint (30) states that the number of hired vehicles should not exceed $h$. Constraints (31)-(33) not only ensure flow balance but also eliminate sub-tours. Constraint (34) computes arrival time at each MS, and constraint (35) computes tour time duration. Finally, constraint (36) enforces the time window limitation, and constraint (37) defines the domains of the decision variables.

#### *4.1.3. Phase 3: Actual production scheduling*

RMFR returns actual presence time ($Z_{is}$), which gives different values for each scenario. Now, in each MS, production schedulers can solve their production scheduling problem using the values of $Z_{is}$ . For this purpose, an actual scheduling problem model (ASPM) should be solved to produce actual results for each scenario. This model can be solved in a parallel way for each MS $i \in I$ , $Z_{is}$ $s \epsilon S$ . Therefore, the actual delay for each scenario is different because arrival time is a scenario-based parameter. ASPM is formulated as follows:

$$Min\ Z = \sum_{n=1}^{N} DL_n \tag{38}$$

Subject to (28)-(35), (37)-(38), and:

$$SE = C_{km} - Z_{is} \qquad \forall\, m = SPM \in M\,, \forall\, k \in K \tag{39}$$

$$Z_{is} = C_{1m} - \sum_{n=1}^{N} p_{nm} X_{n1} \qquad \forall\, m = SPM \in M \tag{40}$$

#### *4.1.4. Phase 4: Adjustment*

The time window violation cost rate ($\omega$) and coefficient of objective function variance ($\lambda$) play a significant role in solution quality. To find solutions with lower TW violations, the value of $\omega$ should be increased. On the other hand, to reach solutions with a smaller variation, the value of $\lambda$ should be raised. Finding the best value for the penalty rates depends on decision makers' preferences and sensitivity analysis results for the parameter.

## 5. EXPERIMENTAL EVALUATION

This section introduces the input data generation procedure and the optimization approach's implementation results. To see the decision-making algorithm's performance, several instances are solved using CPLEX exact solver embedded in the GAMS 31.1.1 (General Algebraic Modeling System) software [39].

As a notation utilized in the paper, AiBnCmDh corresponds to a test problem with A maximum number of jobs in each MS, B number of potential MSs, C number of machines, and D number of available MFs. It is worth mentioning that each instance has a maximum of $A \times B$ job orders across all MSs in total. The formation of these scenarios is shown in Table 1, and it means that uncertainty parameter, service time ($SE_i$), could be less, equal, and higher than estimated value ($\overline{SE_\iota}$) . Three uncertainty scenarios are defined, which represent optimistic (S1), realistic (S2), and pessimistic (S3) scenarios with a probability of 30%, 40%, and 30%, respectively. Table 2, the randomly generated distribution of different parameters of the proposed model is reported.

*Table 1: Scenario generation*

| Scenario | Uncertain parameter ($SE_i$) value | Probability |
|---|---|---|
| S1 | $0.75 \times \overline{SE_\iota}$ | 30% |
| S2 | $\overline{SE_\iota}$ | 40% |
| S3 | $1.25 \times \overline{SE_\iota}$ | 30% |

*Table 2: Parameters of the model*

| Parameter | Value | Parameter | Value |
|---|---|---|---|
| $p_{nm}$ | $\sim U(2{,}6)$ | $\beta$ | 6 €/Km |
| $q_n$ | $\sim U(10{,}20)$ | $\alpha$ | 10 €/Km |
| $dc$ | 100 | $\bar{v}_{ij}$ | $\sim U(10{,}70)$ |
| $di_{ij}$ | $\sim U(100{,}1000)$ | $du_n$ | $\sim U(50{,}250)$ |
| $\omega$ | 150 €/h | $\lambda$ | 10 |
| M | 1000 | $h$ | $\{2{,}3\}$ |

In order to show the RDDMA performance, three instances were solved. In Table 3, the results of the implementation of Phase 1 is reported. The most important output of this phase is the TW proposal for each MS. As can be seen in this table, expected service time (SE), earliest start (ES), and (LS) are reported, which reveal the desired TW to start operation at each MS.

*Table 3: Results of Phase 1*

| Instance | MS | No. of jobs | SPM position | SE (h) | ES (h) | LS(h) |
|---|---|---|---|---|---|---|
| | 1 | 3 | 2 | 9 | 4 | 97 |
| | 2 | 5 | 2 | 20 | 3 | 48 |
| 5i5n3m2v | 3 | 4 | 1 | 16 | 0 | 57 |
| | 4 | 2 | 3 | 8 | 8 | 57 |
| | 5 | 5 | 2 | 25 | 2 | 44 |
| | 1 | 4 | 2 | 20 | 2 | 79 |
| | 2 | 8 | 3 | 38 | 4 | 51 |
| | 3 | 10 | 2 | 39 | 2 | 67 |
| 7i10n4m2v | 4 | 6 | 4 | 24 | 14 | 51 |
| | 5 | 8 | 1 | 30 | 0 | 79 |
| | 6 | 9 | 2 | 34 | 2 | 66 |
| | 7 | 7 | 3 | 34 | 4 | 67 |
| | 1 | 7 | 2 | 24 | 2 | 103 |
| | 2 | 10 | 3 | 47 | 6 | 49 |
| | 3 | 6 | 2 | 29 | 3 | 44 |
| | 4 | 6 | 3 | 22 | 6 | 97 |
| | 5 | 7 | 1 | 30 | 0 | 93 |
| 10i10n3m3v | 6 | 8 | 2 | 37 | 2 | 69 |
| | 7 | 9 | 3 | 34 | 5 | 46 |
| | 8 | 7 | 2 | 26 | 2 | 68 |
| | 9 | 10 | 2 | 32 | 2 | 47 |
| | 10 | 8 | 1 | 30 | 0 | 38 |

After receiving the results of Phase 1, the RMFR problem can be solved using the desired TW proposed by each MS to reveal the response variable values. In Table 3, the results of Phases 2 and 3 are reported. As shown in Table 4, arrival time, delay, and actual delay may change in each scenario, but the robust optimization approach tries to minimize their variation. On the other hand, since routing is a structural decision variable, routes remain unchanged in different scenarios (see Table 5).

*Table 4: Results of Phases 2 and 3*

| Instance | | $Z_{is}$ (arrival time) | | | $U_{is}$ | | | Actual delay (Avg.) | | | CPU |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | MS | S1 | S2 | S3 | S1 | S2 | S3 | S1 | S2 | S3 | |
| 5i5n3m2v | 1 | 8 | 8 | 8 | 0 | 0 | 0 | 0 | 0 | 0 | 3s |
| | 2 | 45 | 56 | 67 | 0 | 8 | 19 | 0 | 8 | 28 | |
| | 3 | 20 | 22 | 24 | 0 | 0 | 0 | 0 | 0 | 0 | |
| | 4 | 36 | 45 | 54 | 0 | 0 | 0 | 0 | 0 | 0 | |
| | 5 | 7 | 7 | 7 | 0 | 0 | 0 | 0 | 0 | 0 | |
| 7i10n4m2v | 1 | 42 | 52 | 62 | 0 | 0 | 0 | 0 | 0 | 0 | 8s |
| | 2 | 74 | 88 | 103 | 23 | 37 | 52 | 36 | 82 | 142 | |
| | 3 | 7 | 7 | 7 | 0 | 0 | 0 | 0 | 0 | 0 | |
| | 4 | 16 | 16 | 16 | 0 | 0 | 0 | 0 | 0 | 0 | |
| | 5 | 74 | 89 | 104 | 0 | 10 | 25 | 0 | 10 | 25 | |
| | 6 | 43 | 49 | 55 | 0 | 0 | 0 | 0 | 0 | 0 | |
| | 7 | 118 | 141 | 166 | 51 | 74 | 99 | 46 | 113 | 219 | |
| 10i10n3m3v | 1 | 34 | 42 | 48 | 0 | 0 | 0 | 0 | 0 | 0 | 59s |
| | 2 | 69 | 84 | 100 | 20 | 35 | 51 | 47 | 107 | 197 | |
| | 3 | 7 | 7 | 7 | 0 | 0 | 0 | 0 | 0 | 0 | |
| | 4 | 16 | 16 | 16 | 0 | 0 | 0 | 0 | 0 | 0 | |
| | 5 | 70 | 83 | 96 | 0 | 0 | 3 | 0 | 0 | 3 | |
| | 6 | 42 | 47 | 53 | 0 | 0 | 0 | 0 | 0 | 0 | |
| | 7 | 119 | 146 | 174 | 73 | 99 | 128 | 288 | 523 | 775 | |
| | 8 | 85 | 99 | 114 | 17 | 31 | 46 | 17 | 31 | 51 | |
| | 9 | 40 | 47 | 55 | 0 | 1 | 8 | 0 | 1 | 15 | |
| | 10 | 9 | 9 | 9 | 0 | 0 | 0 | 0 | 0 | 0 | |

*Table 5: Results of Phase 2*

| Instance | Routes | $\xi_s$ (Objective function) | | |
|---|---|---|---|---|
| | | S1 (€) | S2 (€) | S3 (€) |
| 5i5n3m2v | MF1: 0-1-3-0<br>MF2:0-5-4-2-0 | 12865 | 13085 | 13305 |
| 7i10n4m2v | MF1:0-3-1-5-0<br>MF2:0-4-6-2-7-0 | 18916 | 19446 | 20016 |
| 10i10n3m3v | MF1:0-3-1-5-0<br>MF2:0-4-6-8-0<br>MF3:0-10-9-2-7-0 | 28223 | 28973 | 29773 |

In order to complete phase 4, a trade-off between TW violation ($\sum_{s\epsilon S}\sum_{i\in I} p_s U_{is}$) and the MF fleet costs ($\sum_{s\epsilon\Omega} p_s \xi_s$) should be performed using a sensitivity on the value of $\omega$ (TW violation cost rate). Figures 4,5 and 6 demonstrate the results of adapting various values of $\omega$ for different instances. Setting higher values of $\omega$ results in more robust solution and guarantees lower delay even in the pessimistic scenarios. For example, in Fig 6 (10i10n3m3v) the results show that reaching less than 118h TW violation is not possible and, considering the fleet costs, it is better to set $\omega$ between 50 to 150 €/h to find an acceptable decision for both main agents of the problem. Furthermore, almost the same pattern can be seen in the other instances.

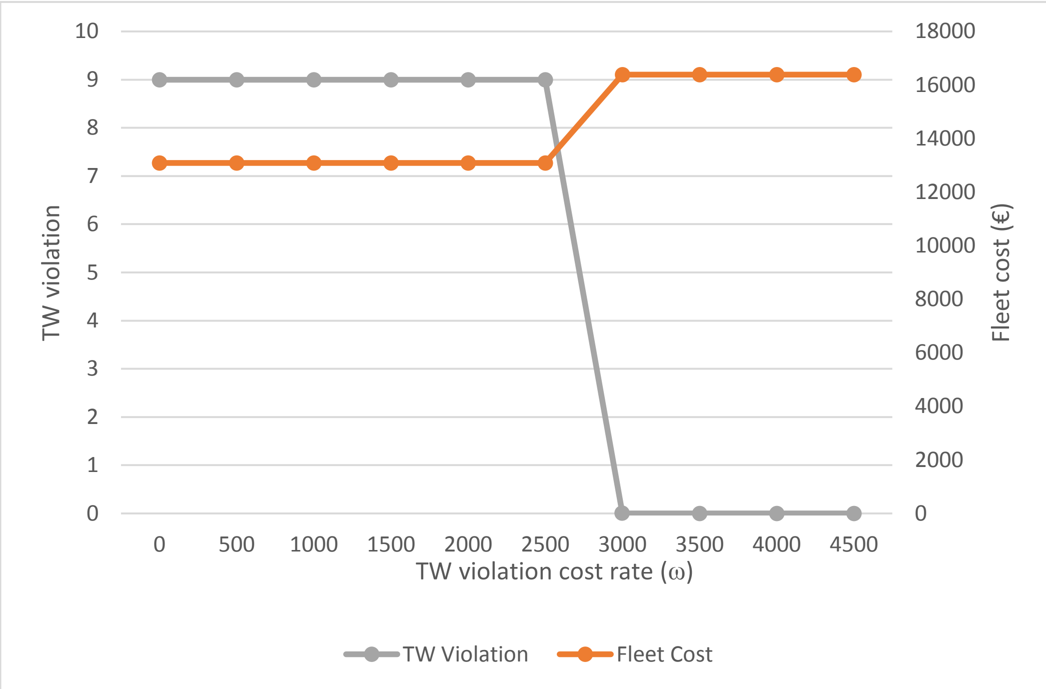


*Fig. 4: Results of Phase 4 (5i5n3m2v)*

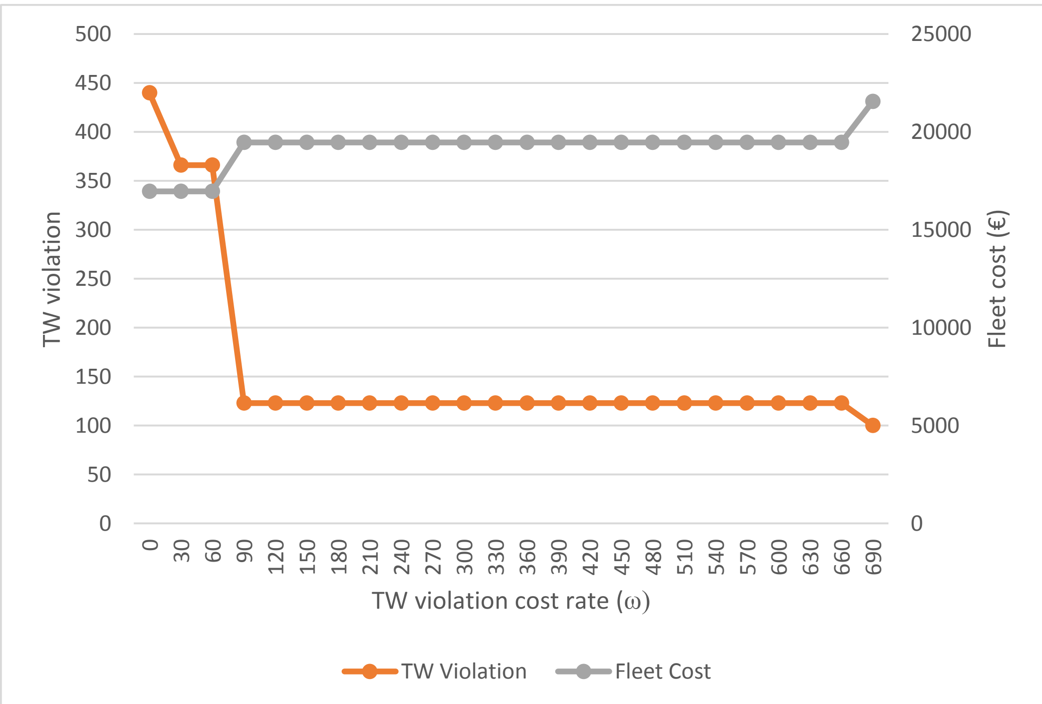


*Fig. 5: Results of Phase 4 (7i10n4m2v)*

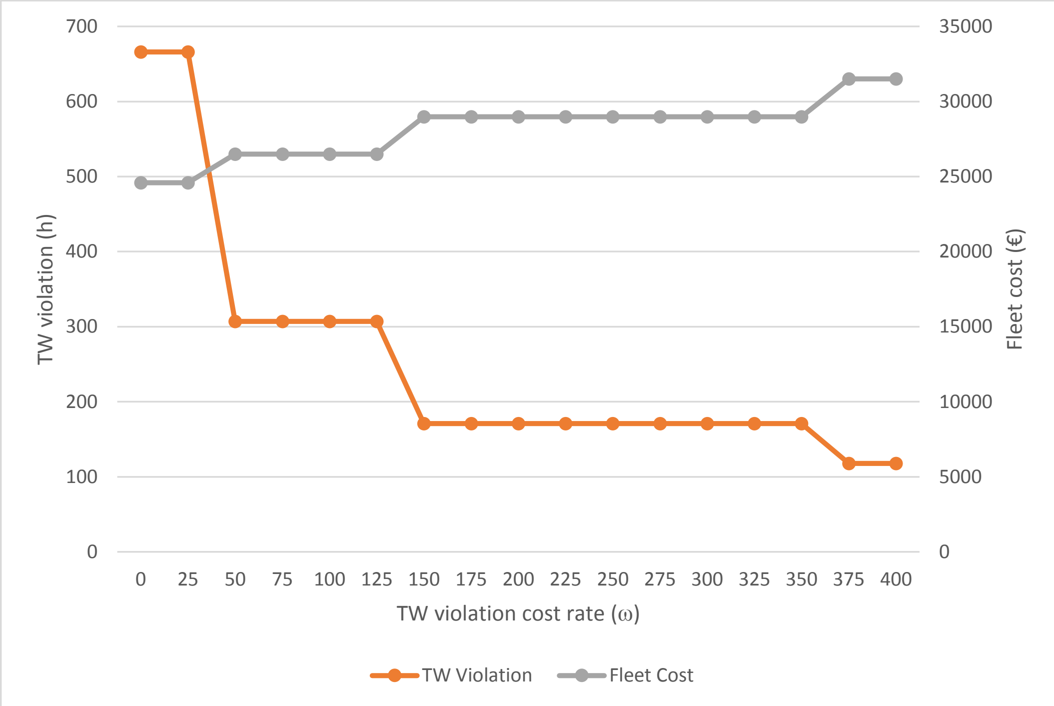


*Fig. 6: Results of Phase 4 (10i10n3m3v)*

## 6. CONCLUSIONS

In this paper, a robust decentralized decision-making approach for the MSC routing production problem was presented. The decentralization approach was developed using a well-known method, namely ATC. Accordingly, four mathematical models were developed to link the created models via the suggested procedure. The RDDMA consists of four phases: Time window determination, robust mobile factory routing, actual production scheduling, and adjustment. Furthermore, to tackle the problem uncertainty, a scenario-based robust optimization method was utilized, which can consider different probable values of the uncertain parameter (service time) in realization. Finally, RDDMA performance was evaluated by several instances and experimental results. The outputs show that using sensitivity analysis on TW violation cost rate, a Pareto frontier can be provided for decision makers to find their preferred solution. For future research, solving large-scale instances and using an adjustable robust optimization method are suggested.

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