

Graphical Abstract

Actor-based Large Neighborhood Search for weekly maintenance scheduling

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Highlights

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- How to allow direct and real-time integration into an optimization process?
- How to perform optimization in a real-time changing parameter space?

Actor-based Large Neighborhood Search for weekly maintenance scheduling

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^a*Technical University of Denmark, Anker Egelundsvej 1, Kongens Lyngby, 2800, Hovedstaden, Denmark*

^b*Technical University of Denmark, Anker Egelundsvej 1, Kongens Lyngby, 2800, Hovedstaden, Denmark*

^c*Technical University of Denmark, Anker Egelundsvej 1, Kongens Lyngby, 2800, Hovedstaden, Denmark*

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^g*Technical University of Denmark, Anker Egelundsvej 1, Kongens Lyngby, 2800, Hovedstaden, Denmark*

Abstract

Several problems facing the operations research field have proven difficult to solve due to their inherent uncertainty and highly dynamic nature. Stochastic optimization, fuzzy logic, and robust optimization are some of the methods that have been proposed to solve these issues. These methods make an implicit assumption on static data and a static problem setting. Maintenance scheduling is one such problem where the best available information continually updates and then therefore the scheduling continuously needs to be updated. Maintenance scheduling is a complex process and its correct implementation is usually more associated with operation management, but this paper will argue that it is possible to implement general maintenance scheduling approaches if the solution method is designed to be integrated into a business process of the kind that are usually developed by the principles of operation management.

This paper proposes a novel optimization method that is capable to opti-

mizing a scheduling problem in the following setting: primary data source is changing in real-time; external inputs affects the optimization process; multiple actors are making interdependent decision whose objectives may differ significantly. The proposed solution approach is an actor-based implementation of the large neighborhood search metaheuristic and the paper will show that this approach can naturally model the dynamic nature of operational problems.

Keywords: Large Neighborhood Search, Actor Framework, Real-time Optimization, Human-centered Computing, Interactive Systems and Tools, Decision Support Systems, Interactive Optimization.

1. Introduction

Maintenance scheduling is a dynamic and operational problem and have proven hard to solve and study in operation research due to the need of tight integration with tacit knowledge of decision makers and the way that industry usually assigns responsibility for decision-making to an individual representing only a small part of the complete process.

These multiple smaller processes are often difficult to map to a single mathematical model describing the whole system as elaborated by ((Barthélemy et al., 2002)). Solving operation research problems that are operational in nature have additional requirements over conventional static problems: they have to be responsive to changing parameters; able to be assimilated into the decision-makers workflow; allow for integration with dynamic data sources such as databases and RESTapi (Meignan et al., 2015). Operational aspects of operation research, as opposed to higher level strategic and tactical aspects, are characterized by extensive amounts negotiation and feedback on proposed schedules. The lack of integration and responsiveness can lead to schedules that are not directly implemented in practice but instead provides initial suggestions Meignan et al. (2015), which are then iterated else where in the scheduling process. In (Barthélemy et al., 2002) the authors argue that many problems that operation research aim to solve are often composed of a group of individuals whose decisions are consolidated into an "epistemic subject" for which a mathematical model can be formulated and solved, with many scheduling problems being good examples. Furthermore, some multi-objective optimization problems are a product of there being multiple actors in the decision making process each with different views on an optimal sched-

ule from their vantage point rather than there being actual multiple objectives for each individual actor.

This paper proposes a solution method that will allow for real-time optimization based on actor/user interaction and connection to a dynamic data source, effectively meaning changes to the parameter space. The proposed solution method will be tested on the multi-compartment multi-knapsack problem (MCMKP) on a large dataset from a maintenance performing company. The MCMKP naturally models what in the practical maintenance is called the weekly schedule, taken form (Palmer). It should be noted that the scientific maintenance scheduling literature deviates significantly from its practical implementation which is detailed in (Palmer). The solution method will be based on the large neighborhood search (LNS) metaheuristic. This meta heuristic was chosen due to its properties of naturally being able to work with and fix infeasible solutions and its state of the art performance on various scheduling problems.

To understand the need for actor-based methods some background knowledge will be required about the maintenance scheduling process. In figure 1 illustrates the general setup of a healthy maintenance planning and scheduling system. The systems actors have the following responsibilities: the planner generates the work orders that are to be scheduled; the scheduler creates weekly schedules based on a knapsack formulation; based on the weekly schedule the supervisor assigns work order activities that the work order is composed of (the assignment problem); the technicians executes the work in sequential pattern (single machine scheduling). A final point on the necessary of actor-based approaches to model should a setup is the idea of ownership of a work order. Throughout the scheduling process a work order is owned by a specific actor and he alone is allow to modify it. This means that a single model approach is very difficult to implement in practice as a work order looks different depending on the actor that currently owns it. This also highlight another an point in maintenance scheduling: that the stochastic nature of the maintenance scheduling process handled using a change of model each with different levels of aggregation, opposed to more academic approaches such as fuzzy logic and stochastic optimization.

When the fundamental uncertainties manifest themselves during planning or execution work orders are rescheduled by moving between the different actor (models), meaning that the stochastic elements of maintenance scheduling are handled by dynamic rescheduling between the actors.

The paper is divided into four different sections. Section 2 explains the

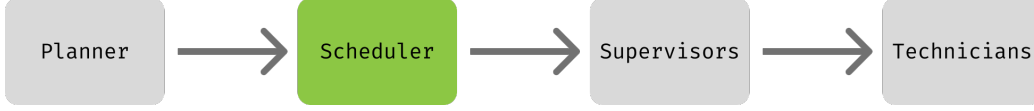


Figure 1: Simple overview of the scheduling process with its primary types of actors. The planner, the scheduler, the supervisor(s), and the technicians. The green color highlights the scheduler as it the actor in the maintenance scheduling process that is the foundation for the paper.

weekly maintenance scheduling model in detail and forms the foundation of the paper. Section 3 shows that results coming from the implemented system where the implementation will be affected by simulated user-interaction. Section 4 will discuss the implications of the research and possible future research directions.

1.1. *The Weekly Schedule: Multi-compartment Multi-knapsack Problem with capacity penalties*

The actor-based large neighborhood search is implemented on the MCMKP which models that weekly schedule in maintenance. The model is comprised of five different sets. P is the number of weekly periods; W is the number of work orders; τ is the number of different traits; E is a set that defines which work orders should be excluded from a specific weekly period; I is an inclusion set that defines the allocation of specific work orders which should be included in a specific weekly period. The model has four parameters. v_{pw} is the value of work order w in weekly period p ; d is the penalty for exceeding a specific trait capacity; $c_{w\tau}$ is the capacity requirement for work order w for trait t ; $cap_{p\tau}$ is the total amount of capacity available in for weekly period p for for trait t . The model has 2 decision variables. x_{wp} , is a binary decision variable equal to one if work order w is in weekly period p and zero otherwise; $pen_{p\tau}$ is non-negative decision variable equal to the amount of excess capacity above the $cap_{p\tau}$ in weekly period p for trait τ . The parameters v , cap , Q , and P are functions of time, τ , in this case as they will be subject to change during the solution process.

$$\text{Min} \quad \sum_{w=1}^W \sum_{p=1}^P v_{wp}(t) \cdot x_{wp}(t) + \sum_{p=1}^P \sum_{\tau=1}^T d \cdot \text{pen}_{p\tau}(t) \quad (1)$$

subject to:

$$\sum_{w=1}^W c_{w\tau} \cdot x_{wp}(t) \leq \text{cap}_{p\tau}(t) + \text{pen}_{p\tau}(t) \quad \forall p \in P, \forall \tau \in T \quad (2)$$

$$\sum_{w=1}^W x_{wp}(t) = 1 \quad \forall p \in P \quad (3)$$

$$x_{wp}(t) = 0 \quad \forall (w, p) \in E(t) \quad (4)$$

$$x_{wp}(t) = 1 \quad \forall (w, p) \in I(t) \quad (5)$$

$$x_{wp}(t) \in \{0, 1\} \quad \forall w \in W, \forall p \in P \quad (6)$$

$$\text{pen}_{p\tau}(t) \in \mathbb{R}^+ \quad \forall p \in P, \forall \tau \in T \quad (7)$$

The objective function 1 minimizes the total weight of all work order assignments together with the penalty d for exceeding the capacity given in constraint 2. Constraint 2 ensures that all the weights $c_{w\tau}$ for each activity in an work order, given that it has been assigned, is lower than the capacity for each period and for each trait τ . $\text{pen}_{p\tau}$ is the amount of exceeded capacity that is needed for the current assignment of work order to be feasible. Constraint 3 makes sure that each work order is assigned to atleast a single period. Constraint 4 excludes a work order from a certain period and constraint 5 forces a specific work order to be in a specific period. Constraint 6 and 7 specify the variable domain for x_{wp} and $\text{pen}_{p\tau}$ respectively. The effects of changing E , I , cap , and v in real-time will be examined to determine their effects on the weekly schedules and objective value.

2. Solution Method

2.1. Actor-based Large Neighborhood Search

A problem which is affected by user-interaction and requires real-time feedback needs an optimization approach that is able to repair infeasible schedules and while also converging quickly. For this the large neighborhood search metaheuristic has been shown satisfy these requirements in the literature Gendreau and Potvin (2019).

The LNS metaheuristic is defined for static problems, meaning that the parameters that make up the problem instance is not subject to change after the algorithm has been started. To make the LNS able adapt to changing parameters in real-time a message system have been implemented into the existing framework. This extension is shown in algorithm 1.

2.1.1. Messages And Destructors

LNS in its most basic form has one constructor and one destructor which repeatedly destroy and rebuild the schedule. For the AbLNS we will generalize on this concept by including messages as destructors of the classic LNS implementation. This generalization can be seen as being somewhat similar to how the adaptive LNS (ALNS) is formulated, but where the different constructors and destructors are chosen externally as well.

Extending on the classic setup we define the following set of destructors, M :

- m_1 : Inclusion destruct message
- m_2 : Exclusion destruct message
- m_3 : Capacities destruct message
- m_4 : Weights destruct message
- m_5 : Random destruct message

Each of these messages affect different parts of the MCMK problem (weekly schedule). Notice here that the first four messages destruct the solution by changing the parameter space and the last message is a random destructor.

Generalizing the destructors from being static structures into messages allows the solution to change in real-time to a changing parameter space

meaning that the algorithm does not need to restart to handle changes in data.

Algorithm 1 Actor-based Large Neighborhood Search

```

1: Input queue = message queue
2: Input P = problem instance
3: Input x = initial schedule
4: while true do
5:   while queue.has_message() do
6:      $P.update(m)$ 
7:      $x.destruct(m)$ 
8:   end while
9:    $x^t = x.repair()$ 
10:  if  $c(x^t) < c(x)$  then
11:     $x = x^t$ 
12:    queue.send(x)
13:  end if
14:  queue.push( $m_5$ )
15: end while
16: return  $x^b$ 

```

The basic LNS setup have here been extended with a ‘message queue’. This message queue will be read from on every iteration of the LNSs main iteration loop. Here we notice that the incoming message are able to change both the solutoin but also the problem instance itself. Here we see one of the defining features of the LNS metaheuristic in play, that due to its inherrent property of being able to optimize a solution that have become infeasible which is something that is very likely to happen when you change the parameter of the problem instance itself.

Another less obvious property the message queue allows is for the algorithm to run indefinitely and instead of restarting the algorithm you instead pass messages to it to allow it be adjust both the solution space and the parameter space. This property avoid the issue of time consuming initial convergence as the algorithm will be found in an optimal state when the solution is perturbed.

3. Results

The results section will: 1. introduce the real-world data instance; 2. show the effect of forcing item set in the specific weekly schedules; 3. show the effect of changing the period capacities, and 4. show the effect of dynamically changing the value of the work orders v .

3.1. Data Instance

| | Number of Item Sets | Number of Compartments | Number of Knapsacks |
|------------|------------------------|---------------------------|------------------------|
| Instance 1 | 3487 | 16 | 52 |

Table 1: Table Caption

3.2. Response to Inclusion

The response to the inclusion of a work order is given by I parameter of the model which is constrained in 5 of model given in 1.1.

The inclusion is made of forcing certain allocations of work orders to be in specific periods. Below a table is provided to show what changes will occur and at what and at what point in time.

| | At Time: 01:00 | At Time: 02:00 | At Time: 03:00 | At Time: 04:00 | At Time: 05:00 |
|-------------|-------------------|-------------------|-------------------|-------------------|-------------------|
| $\Delta P $ | 10 | 20 | 30 | 40 | 50 |

With the inputs defined we will explain the main results which are shown in the figure below.

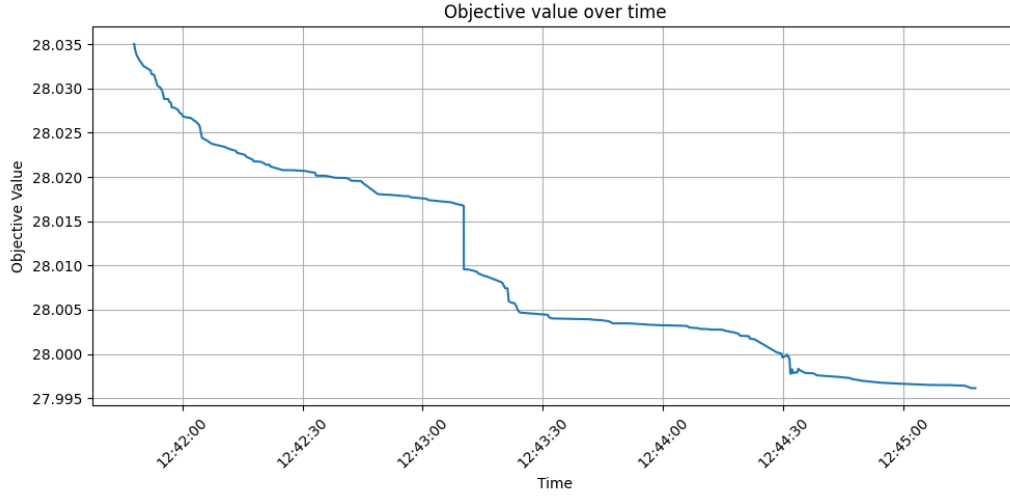


Figure 2: Figure Caption

3.3. Response to Exclusion

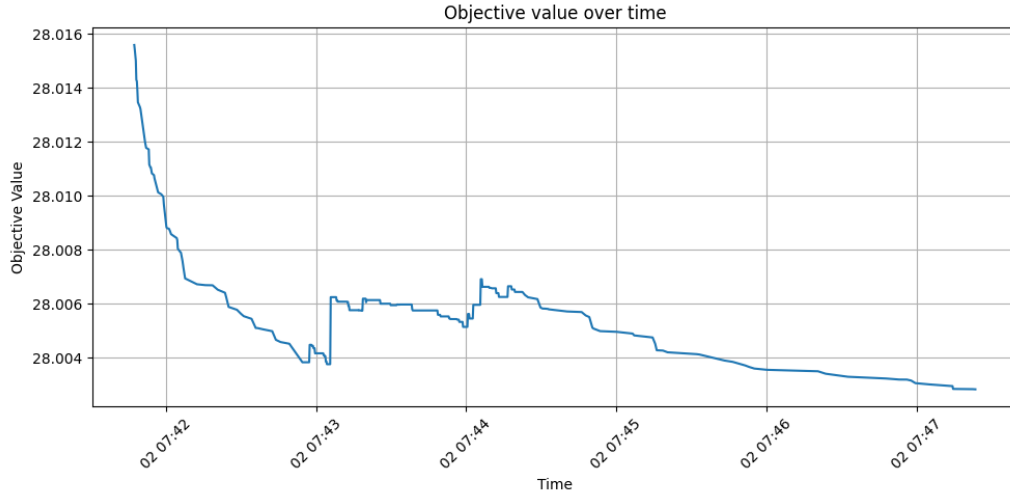


Figure 3: Figure Caption

3.4. Response to Changes in Knapsack Capacities

The effects of changes to capacities will be illustrated in the same way as it was with the response to inclusion and below we see the table that shows which inputs that the AbLNS will be affected by.

| | At Time: 01:00 | At Time: 02:00 | At Time: 03:00 | At Time: 04:00 | At Time: 05:00 |
|----------------|-------------------|-------------------|-------------------|-------------------|-------------------|
| $\Delta p $ | 16 | 16 | 16 | 16 | 16 |
| $\Delta \tau $ | 16 | 16 | 16 | 16 | 16 |
| $\Delta cap $ | 100 | 200 | 400 | 800 | 1600 |

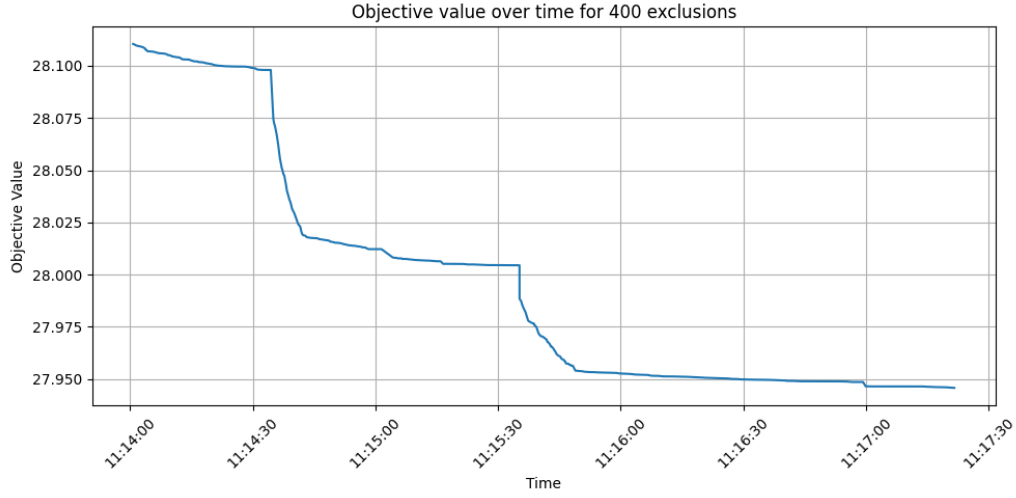


Figure 4: Figure Caption

Correspondingly we also have the figure below in which the resources are decreasing.

3.5. Response to Changes in Item Weights

The final parameter that will be changed is the work order value v . This section will be more elaborate as we have to show how that the work orders are rearranged due to the changes in their value across the different periods.

| | At Time: 01:00 | At Time: 02:00 | At Time: 03:00 | At Time: 04:00 | At Time: 05:00 |
|-------------|-------------------|-------------------|-------------------|-------------------|-------------------|
| $\Delta w $ | 20 | 40 | 80 | 160 | 320 |
| $\Delta p $ | 26 | 26 | 26 | 26 | 26 |
| $\Delta v $ | $1 \cdot 10^5$ | $2 \cdot 10^5$ | $4 \cdot 10^5$ | $8 \cdot 10^5$ | $1.6 \cdot 10^6$ |

4. Discussion

Maintenance scheduling efficiently solves a complex scheduling problem by the use of multiple actors. Through the use of actors the process handles uncertain that is difficult to reason about using models with different levels of aggregation where each actors understands how to exploit his model to the fullest. As the uncertainties manifest themselves the actors/models handle the uncertainty through communication. To further understand the implications of the approach the discussion will be divided into three sections: 1. actors and integration; 2. continuous optimization allows asynchronous optimization; 3. future research.

4.1. Actors & Integration

Often in operation research the failure to reliably solve industry problems are not due to the problems being computationally intractable but more a practical problem of connecting data streams so that the solution approach is connected to dynamic data source of the company and then connecting the solution approach(s) to the relevant stakeholder (actors) through a relevant interface. The actor-based approach proposed in this paper makes integration easier by naturally encapsulation a model with a reliable interface. To better understand the novel properties of this consider the extension of figure

1

as shown in figure 4.1.

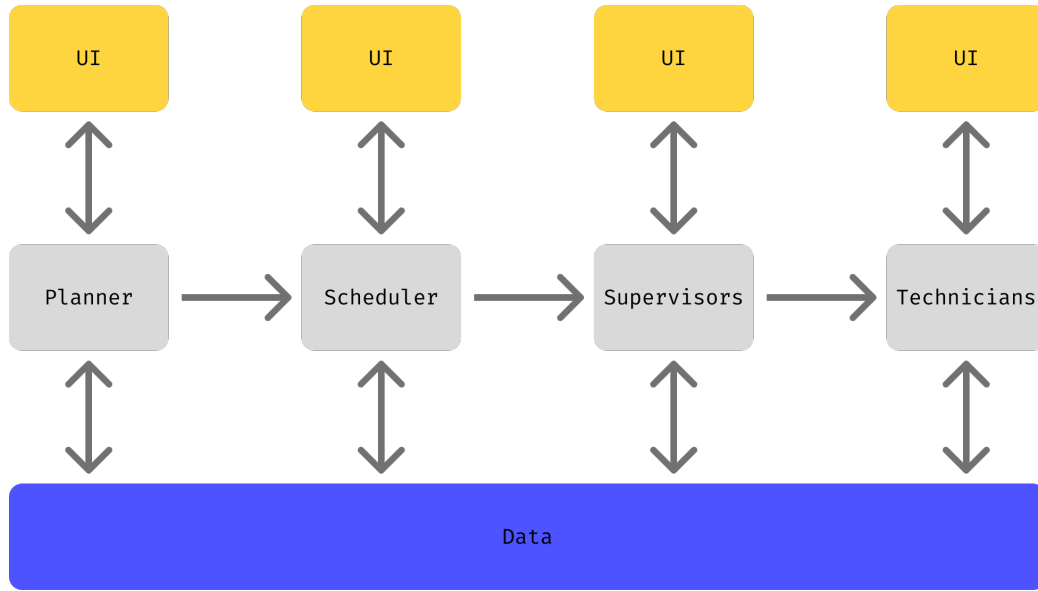


Figure 5: Overview of the scheduling process when modelled as actors. When LNS is encapsulated as an actor it becomes possible to optimize parts of a large process individually instead of optimizing the scheduling problem globally from a single model implementation.

4.2. Continuous Optimization

With actor-based metaheuristics it becomes simple to extend a metaheuristic to run indefinitely with it being able to optimize based on the latest best available information. This may seem like a minor detail as you could argue that you should only ever optimize the schedule when there is an explicit need for it, but consider the case when you start adding more than two actor to a scheduling system, then there arises a need to coordinate people in time as each will have to run their optimizer on after another.

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