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PREDICTIVE DECISION MODELS FOR AN ENERGY EFFICIENT OPERATION OF STACKER CRANES IN A HIGH-BAY WAREHOUSE

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ABSTRACT

This paper presents a simulation-based optimization framework to find and evaluate optimal storage plans in a high-bay warehouse. The two objectives under consideration are reducing the total energy consumption and maximizing the recuperation of energy of stacker cranes. These cranes operating in different aisles are connected by an internal circuit. One part of the framework simulates the power flows both on a single stacker crane and in the internal circuit. Based on that, the optimization part computes energy optimal trajectories for prescribed movements using a variational approach. By dividing the trajectories into time intervals, a mixed-integer programming (MIP) model delivers double-cycle plans. For longer down movements the shape of optimal trajectories would be technically disadvantageous which requires alternatives to avoid the abrasion of the devices.

1 INTRODUCTION

Developing holistic approaches to complex systems is, on the one hand, a central concern of logistics. On the other hand, dealing with such approaches is one of the strengths of simulation models, so that both sides continually inspire each other. The term "complex" here means that in a system at least two phenomena are considered to be equally important, without one dominating the other and one being able to be neglected in favor of the other paying a low price. In this paper, we investigate the energy-optimal operation of stacker cranes in a high-bay warehouse, linking the microscopic time-continuous view of trajectory optimization with the macroscopic event-discrete perspective of order planning. The practical relevance arises in particular from the fact that stacker cranes largely determine the energy consumption of a warehouse due to their necessary dimensions. Figure 1 gives an impression of such cranes. High fluctuations in power consumption cause high costs, and the occurrence of power peaks requires larger wires. Energy storage systems to smooth the power profiles cause costs as well and, clearly, such systems are not able to store energy without losses. The proposed avenue is to operate in such a manner that as much as possible of the energy is directly used. Simulation-based optimization therefore provides valuable contributions to a well-founded cost-benefit analysis.

Another consequence of the high practical relevance is the large number of diverse publications in this area. A recent review about simulation optimization provide Ghasemi et al. (2024) which examines existing production scheduling problem features, optimization frameworks, simulation tools, validation strategies and research gaps. In addition, future aspects related to Industry 4.0 are discussed as well. For a review of green warehousing we refer to Perotti and Colicchia (2023) who proposed green strategies and main fields for improving environmental sustainability of logistics sites, especially material handling and operational practices. Furthermore, measures for energy efficiency are developed and analyzed. Looking at research articles, a key topic is the improvement of sustainability via energy efficient scheduling in automated storage and retrieval systems. For instance, Roshan et al. (2019) developed a class-based allocation strategy. Rajković et al. (2017) consider multiple objectives – namely costs, travel time and CO_2 emission. The bi-objective approach of considering travel time and energy consumption of Yang et al. (2023) is slightly different. The works of Grüttemeier et al. (2023) and Rams et al. (2017) put special

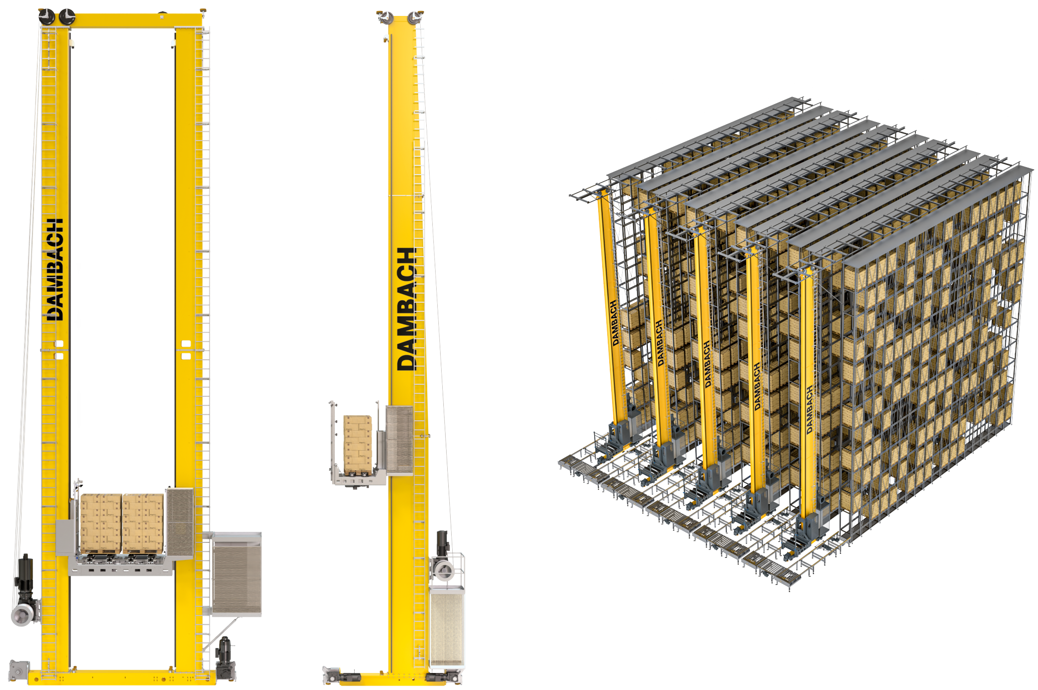


Figure 1: A single stacker crane (left) and a scheme of a warehouse with four aisles (right). The total mass of up to 40 tons in combination with heights of 30 meters lead to peak powers of several 100 kW (credit: DAMBACH GmbH & Co. KG).

attention to the motion planning of cranes. Regarding the electrical aspects of the problem, simulation of circuits (e. g. using equivalent circuit diagrams) is now standard, see (Maksimovic et al. 2001) for a study about converter simulation for instance. Shekhar et al. (2017) put the focus more on the energy efficiency of converters. Besides the converter topic, power peak prediction and power peak reduction play an important role, see Melkowski and Hofmann (2023) for a discussion of capacitors in this context or Rowe et al. (2014) for a control methodology, and Cardenas et al. (2009) developed a genetic algorithm. A step further by investigating the relation between logistics and electricity pricing go (Mohsenian-Rad and Leon-Garcia 2010).

The two core parts of the developed model are a certain number of stacker cranes, whose energy-optimal trajectory planning (Section 2.2) is based on a technical model (Section 2.1), and a storage system (double-layer capacitor) – all connected in an internal DC voltage network (Section 2.3), which is fed from the external power supply. Section 2.4 is dedicated to coupling this electro-mechanical model to logistical order planning. This is followed by a collection of selected numerical results in Section 3. We summarize in Section 4.

Our proposed framework efficiently combines techniques of variational analysis with linear MIP models. To find optimal trajectories, we avoid an a priori discretization of the problem which would bloat the computational effort. Instead an Euler-Lagrange approach is applied to compute the shape of a trajectory as a solution of an ordinary differential equation. Based on that, the MIP model yields optimized disposition plans. Therefore, the framework addresses the problem of an efficient warehouse operation by a double optimization (trajectories and schedules). Especially for long down movements, the optimum w. r. t. recuperation turns out to be technically disadvantageous. For such movements, minimizing the energy consumption yields different solutions than optimizing the recuperation.

2 MODEL SETUP

The overall framework is designed to process a list of storage and retrieval tasks, where the shapes of all trajectories as well as the ordering of the tasks are subject to optimizations. As input serves a list of the positions where the items should be stored and retrieved. The output contains a time schedule of the tasks and the profiles of all trajectories as well as the profiles of the energy storage utilization and the grid connection power. The simulation-based optimization framework consists of four parts explained in more detail below. The first two parts refer to a single stacker crane (Section 2.1: simulation of the power flow based on the technical features of the device, Section 2.2: trajectory optimization w. r. t. energy recuperation). The third part is dedicated to the circuit architecture of the warehouse (Section 2.3). The fourth part optimizes the disposition planning (Section 2.4).

2.1 Power Flow of a Single Stacker Crane

Simulating the power supply and demand is crucial for any energy investigations. We established a component-based model mimicking of the power flow beginning with the mechanics directly related to the movement as such and ending up at the part between the drive and the DC circuit. As sketched in

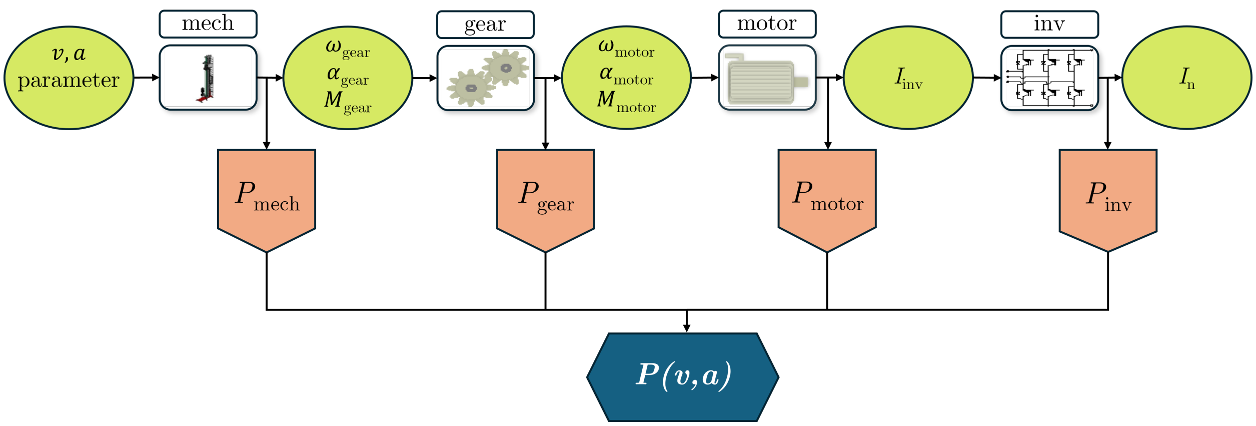
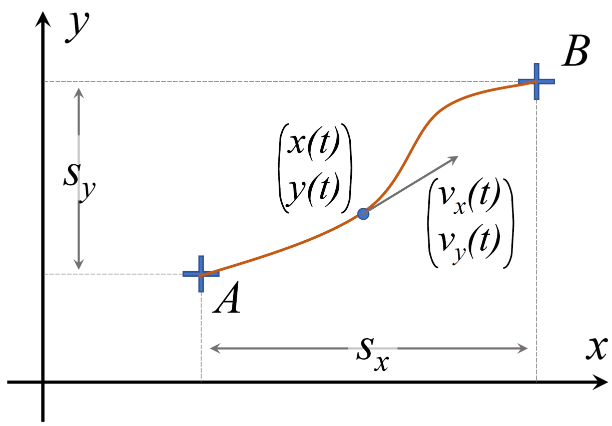


Figure 2: Scheme of the power flow model for one power train (either running gear or lifting gear) of a stacker crane. The velocity v and the acceleration a together with the technical parameters (especially the load mass) serve as input and are subsequently transformed into angular velocities ω, accelerations α and momentums M; eventually all power components are added up and the final current I_n is evaluated, see (Schützhold et al. 2014) for details.

Figure 2, there are four components: the mechanics, the gear, the motor and the AC/DC inverter. The relevant mechanical and electrical quantities are handed over, i. e. the velocity v and the acceleration a of the movement serve as input for the mechanical model yielding the first power component P_{mech}. The resulting angular quantities ω_{gear}, α_{gear} as well as the angular momentum M_{gear} are handed over to the second component modeling the gear. Therefore P_{gear} gives the power arising from the gear. The changed quantities ω_{motor}, α_{motor}, M_{motor} are transmitted to the third component (motor) which yields the motor power P_{motor} and the current I_{inv} needed for the calculation of the inverter power P_{inv} as fourth component. Finally, the power components are added up to the total power

$$P(v,a) = P_{\text{mech}} + P_{\text{gear}} + P_{\text{motor}} + P_{\text{inv}} \tag{1}$$

entering the objective function (5) of the trajectory optimization in Section 2.2. The direction sign is chosen such that $P > 0$ means a power demand. The calculation of each component could be rather intricate because not only the features of the engine are included (e. g. the kind of motor as asynchronous machine, or the inverter as two-level-voltage source converter). In addition, dissipative effects as losses due to friction, heat



parameter	running gear x direction	lifting gear y direction
$v_{\max}$	3.0 m/s	0.9 m/s
$a_{\max}$	0.5 m/s^2	0.6 m/s^2
$j_{\max}$	1.0 m/s^3	0.6 m/s^3

Figure 3: Kinematic scheme of the setup of the trajectory optimization, where the vehicle moves from point A to B in such a way that the slower drive travels time minimally and the other drive makes optimal use of the recuperated energy; the table lists the parameter entering (3).

and hysteresis are considered. All in all, one can imagine a power flow model as a cascade of non-linear multi-parameter functions, where – from the mathematical perspective – the most important parameter is the load mass which can vary from travel to travel. Figure 5 in Section 3 shows the total power for both drives of the currently implemented model.

2.2 Trajectory Optimization

This part of the simulation framework optimizes the shape of the trajectory w. r. t. best energy recuperation between both drives of the stacker crane. It combines the energetic aspects explained in Section 2.1 with kinematic conditions of the movements. To not reduce the throughput of the warehouse that one of the drives with the longer travel time (the slow) moves time minimally where the other one (the fast) is adapted as such to reduce the net power flow in both directions. Let us consider a travel from the start A to the goal B within a vertical plane (see Figure 3) with the side conditions

$$\left|v_{x/y}(t)\right| \leq v_{\max}, \quad \left|a_{x/y}(t)\right| \leq a_{\max}, \quad \left|j_{x/y}(t)\right| \leq j_{\max} \tag{2}$$

$$v_{x/y}(0) = v_{x/y}(T) = a_{x/y}(0) = a_{x/y}(T) = 0 \tag{3}$$

$$\int_0^T v_{x/y}(t) = s_{x/y} \tag{4}$$

for the distances $s_{x/y}$, the velocity profiles $v_{x/y}(t)$, the acceleration profiles $a_{x/y}(t)$ and the jerk profiles $j_{x/y}(t)$ (see Figure 3 for the implemented values). Regarding the time minimal movements to overcome s_x and s_y in the first instances leads to the durations T_x and T_y, respectively. Then the time horizon T of the trajectory optimization results from $T = \max\{T_x, T_y\}$. Thus, the velocity profile of the slower drive is fixed by its time minimal movement. The other follows from minimizing the net recuperation expressed as the objective function

$$E(v) := \int_0^T \left|P_{\text{slow}}(t) + P_{\text{fast}}(v,a)\right| \mathrm{d}t \tag{5}$$

Here, both power functions P_{slow} and P_{fast} are taken from Section 2.1.

Applying advanced methods of calculus reduces the infinite-dimensional problem to the non-linear less-dimensional problem of finding a time grid $0 = t_0 < t_1 < \ldots < t_n = T$ where for each interval $[t_i, t_{i+1}]$ exactly one of the following cases applies:

A) The dynamics is given by an active constraint, i. e. either v, a or j achieves its limit, see Equation (2).

B) The power flows of both drives cancel out exactly which is equivalent to the implicit differential equation

$$P_{\text{slow}}(t) + P_{\text{fast}}(v(t), \dot{v}(t)) = 0 \tag{6}$$

to be solved for v (where $a(t) = \dot{v}(t)$). Clearly, this case is very restrictive, so it does not occur practically.

C) Otherwise the profile $v(t)$ is the solution of the Euler-Lagrange equation

$$0 = \frac{\partial P_{\text{fast}}}{\partial v} - \frac{\mathrm{d}}{\mathrm{d}t}\frac{\partial P_{\text{fast}}}{\partial \dot{v}} + \lambda \tag{7}$$

where λ denotes the multiplier arising from (4).

The optimizer solves cases B and C numerically and searches for a twice continuously differentiable function $v(t)$ over the entire interval $[0, T]$ combined of the cases A, B, C which minimizes (5). Shooting methods and Newton's method are used to calculate the grid points iteratively to a sufficiently high precision.

2.3 Electrical Network and Energy Storage Simulation

The electrical network model of the warehouse is shown schematically in Figure 4. From left to right

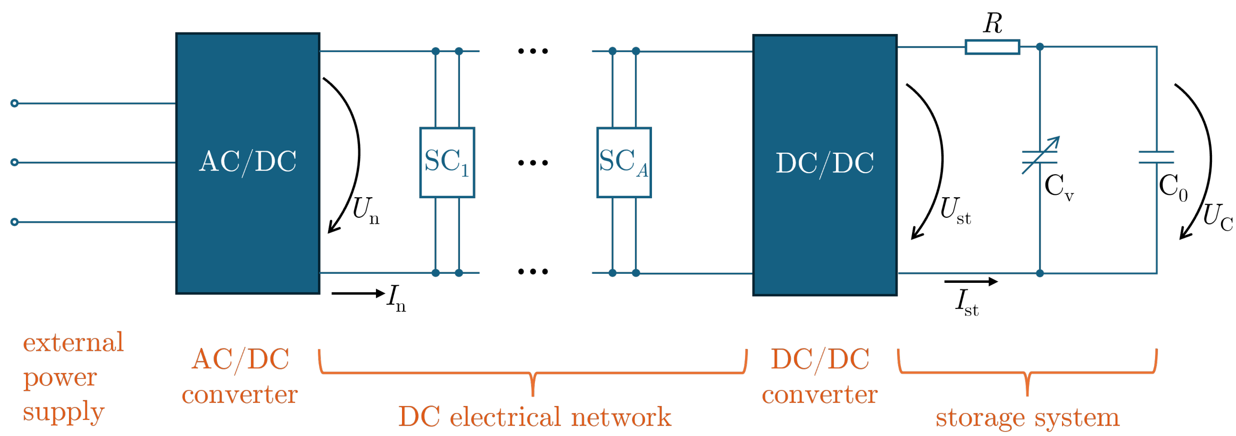


Figure 4: Scheme of the warehouse circuit architecture: the external 3-phase AC current is transformed to the internal DC current; the internal DC network connects all stacker cranes (SC, with two power trains) and via another converter a storage system is included (double-layer capacitor with a variable capacity C_v).

there are the external power supply, the AC/DC converter, several power trains of the stacker cranes (SC), a DC/DC converter for leveling the voltages of the DC circuit and the voltage of the storage (right most part of Figure 4). Both voltages are assumed to be constant. The current that each stacker crane draws from or feeds into the internal circuit follows from the model sketched in Section 2.1. The power loss of the converters is given by algebraic equations à la

$$P_{\mathrm{DC/DC}} \propto \frac{U_{st}}{U_n}(\hat{U} \cdot I_{st} + \hat{R} \cdot I_{st}^2) + U_n^{0.6} \cdot I_{st}^{0.6} + U_n^{1.35} \cdot I_{st} \tag{8}$$

where $\hat{U}$, $\hat{R}$ denote auxiliary parameters. The equation reflects the switching losses of the inverter based on data sheets. Thus, simulating the charging of the double layer capacitor remains as the key part of this section. The fill rate of the storage, encoded via the electric charge q, and the current are governed by the following set of algebraic differential equations

$$U_{st} = R \cdot I_{st} + U_C \tag{9}$$

$$\dot{q} = I_{st} \tag{10}$$

$$q = U_C \cdot (C_0 + \underbrace{\hat{C} \cdot U_C}_{=:C_v}) \tag{11}$$

arising from a power balance.

The storage simulation completes the setup concerning the operative part of the model. Having the storage and retrieval tasks, the time-dependent profiles of all kinematic and electrical quantities can be computed.

2.4 Scheduling of Storage and Retrieval Tasks

We envisage the following scenario: the warehouse contains A aisles (with one stacker crane per aisle) and each of the cranes is given a list of S_a storages and retrievals ($a = 1...A$) to be combined to double cycles. We assume the positions of the storage places to be fixed (and exclude them from the optimization as such). This leads to the question: Regarding each stacker crane, in which way the storages and retrievals should be paired and what is the order of these pairings to either minimize the total energy consumption or to maximize the recuperation?

The main challenge lies in the connection of the operative (time-continuous, microscopic) level (Section 2.2) with the above combinatorial (event-discrete, macroscopic) level which we tackle by introducing a fixed equidistant time grid (consisting of time intervals lasting e. g. 1 s), computing the energy values for all potentially relevant travels (decomposed into these time intervals) and building a linear MIP model with binary decision variables based on this energy data.

To this end, let us introduce the following target variables:

$${}^{a}_{t}x^{ij}_{d} = \begin{cases} 1 & \text{if the } t\text{-th time interval is the } d\text{-th time interval of the double cycle connecting the} \\ & i\text{-th storage point with the } j\text{-th retrieval point (for the } a\text{-th stacker crane)} \\ 0 & \text{otherwise} \end{cases}$$

${}_{t}p \in \mathbb{R}_{\geq 0}$: total energy consumption within the t-th time interval

${}_{t}\tilde{q}, {}_{t}\hat{q} \in \mathbb{R}_{\geq 0}$: positive and negative part of the total recuperation within the t-th time interval

As explained above, the problem parameters are encoded via:

${}^{a}D^{ij} \in \mathbb{N}$: duration of the double cycle connecting storage point i with retrieval point j (for the a-th stacker crane)

$T \in \mathbb{N}$: time horizon of the entire scheduling problem, roughly estimated by $T = \max_{a,i,j} S_a \cdot {}^{a}D^{ij}$ with obvious improvements

${}^{a}P^{ij}_{d} \in \mathbb{R}$: resultant energy demand within the d-th time interval of the double cycle connecting storage point i and retrieval point j, where ${}^{a}P^{ij}_{d} < 0$ indicates an oversupply and ${}^{a}P^{ij}_{d} > 0$ stands for a power demand

with $1 \leq a \leq A$, $1 \leq i, j \leq S_a$, $0 \leq d \leq {}^{a}D^{ij} - 1$ and $0 \leq t \leq T$. The objective functions read as

$$F_{\text{con}} := \sum_{t=0}^{T} {}_{t}p \to \min \tag{12}$$

for minimizing the total energy consumption, and

$$F_{\text{rec}} := \sum_{t=0}^{T} {}_t\tilde{q} + {}_t\hat{q} \to \min \tag{13}$$

for optimizing the recuperation; both subject to the constraints

$$\underset{1\leq a\leq A}{\forall} \quad \underset{1\leq i\leq S_a}{\forall} \quad \sum_{j=1}^{S_a} \quad \sum_{t=0}^{T-{}^aD^{ij}+1} {}^a_t x^{ij}_0 = 1 \tag{14}$$

$$\underset{1\leq a\leq A}{\forall} \quad \underset{1\leq j\leq S_a}{\forall} \quad \sum_{i=1}^{S_a} \quad \sum_{t=0}^{T-{}^aD^{ij}+1} {}^a_t x^{ij}_0 = 1 \tag{15}$$

$$\underset{\substack{1\leq a\leq A\\ 0\leq t\leq T-1}}{\forall} \quad \underset{1\leq i,j\leq S_a}{\forall} \quad \underset{0\leq d\leq {}^aD^{ij}-1}{\forall} {}^a_t x^{ij}_d = {}^{\;\;a}_{t+1} x^{ij}_{d+1} \tag{16}$$

$$\underset{\substack{1\leq a\leq A\\ 0\leq t\leq T}}{\forall} \quad \sum_{i,j=1}^{S_a} \quad \sum_{\tilde{t}=\min\{0,T-{}^aD^{ij}+1\}}^{t} {}^a_{\tilde{t}} x^{ij}_0 \leq 1 \tag{17}$$

$$\underset{0\leq t\leq T}{\forall} \quad \sum_{a=1}^{A} \quad \sum_{i,j=1}^{S_a} \quad \sum_{d=0}^{{}^aD^{ij}-1} {}^aP^{ij}_d \; {}^a_t x^{ij}_d \leq {}_t p \tag{18}$$

$$\underset{0\leq t\leq T}{\forall} \quad \sum_{a=1}^{A} \quad \sum_{i,j=1}^{S_a} \quad \sum_{d=0}^{{}^aD^{ij}-1} {}^aP^{ij}_d \; {}^a_t x^{ij}_d = {}_t\tilde{q} - {}_t\hat{q} \tag{19}$$

Please note that

- the index t measures the global time
- the index d measures the internal time of each double cycle
- constraint (16) connects both time scales and prohibits the interruption of the travels by the logistic order planning, i. e. a phase of halt can only be part of a travel if it follows as a result of the trajectory optimization (although the MIP model decomposes the travels in small time intervals, the sequence of those intervals belonging to one travel must not be interrupted)
- constraints (14,15) both ensure that all points are included once and all double cycles are completed within the global time interval
- constraint (17) ensures that each stacker crane is only occupied by at most one task
- condition (18) filters the pure consumption
- equation (19) equalizes energy consumption and energy recovery to evaluate the recuperation

3 NUMERICAL RESULTS

We start our collection of results with Figure 5 showing the power flow for the power trains of a stacker crane (see Figure 2 as well). The power flow model includes the energy needed for the movement as such as well as dissipative losses. All derivatives of the power function $P(v,a)$ are computed numerically (e. g. for (7)). The next example considers a single trajectory optimization with $s_x = 15$ m, $s_y = 18$ m and a load of 1000 kg (see Figure 6), where the lifting gear moves time minimally and the running gear is adapted. Its velocity profile (Figure 6, middle panel, red solid curve) is mainly a solution of the Euler-Lagrange equation (7), at the boundary of the time interval $[0,T]$ active constraints dominate the behavior.

As a third example, let us consider a scheduling task which we downsize to make it more transparent for the reader (see Figure 7). For each of the two stacker cranes, two storage positions ($\times$ markers) and two retrieval positions (+ markers) are given (formally, $A = 2$ and $S_1 = S_2 = 2$). The left panel shows the optimal

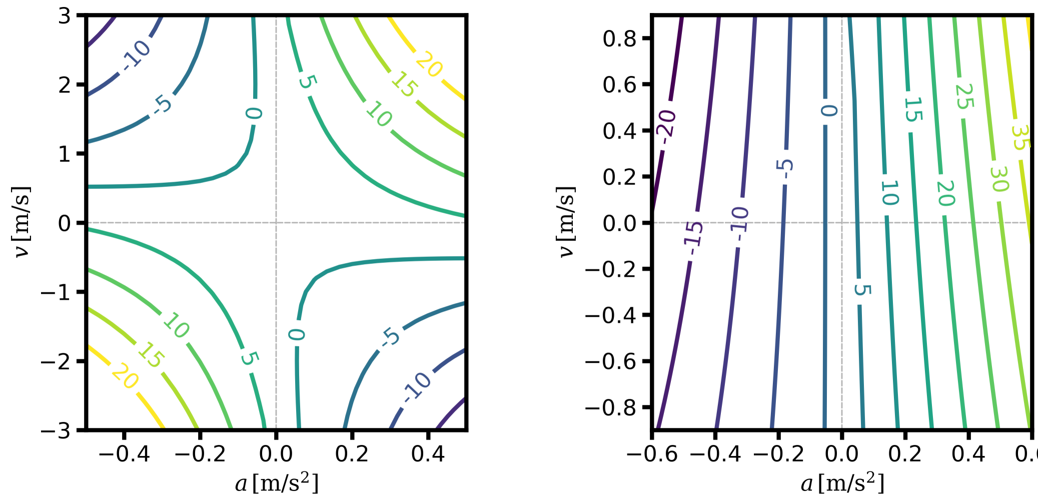


Figure 5: Contour plot of the power $P(v,a)$ according to (1) as a function of the velocity v and the acceleration a for a load mass of 1000 kg (left: running gear, right: lifting gear).

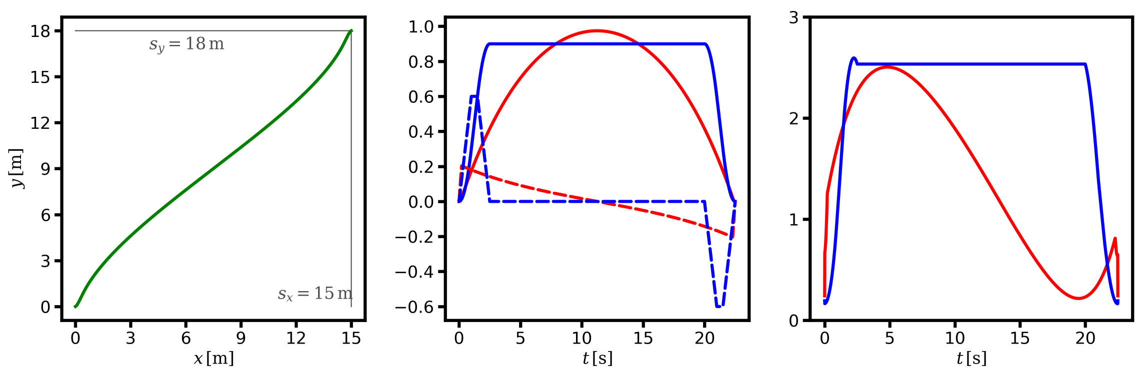


Figure 6: Optimal trajectory in the sense of (5) connecting two points having the distances $s_x = 15$ m and $s_y = 18$ m (left panel) with the respective profiles of the velocity (solid curves, in m/s) and the acceleration (dashed curves; in m/s^2) of the running gear (red curves) and the lifting gear (blue curves) displayed in the middle panel. The power profiles in 10 kW (blue curve) and kW (red curve) are shown in the right panel (same color code).

pairing to double cycles according to the model (8,10-15) of Section 2.4, where all of the trajectories are the result of the optimization discussed in Section 2.2. In addition, the right panel of Figure 7 exhibits the schedule of the two double cycles. Note that the model prohibits the interruption of the double cycles and thus, only whole double cycles can be shifted along the time axis. Since we considered a small problem instance, we used time intervals of length 1 s. Some systematic calculations indicate that the computational time significantly reduces if the time intervals are enlarged.

If one looks at Figure 6 with several trajectories, a special phenomenon of maximizing the recuperation becomes apparent, because it is noticeable that some of these trajectories have a special shape (end of the first double cycle of SC2 and end of the second double cycle of SC1): the horizontal movements oscillate (see left panel) and therefore the net power also fluctuates. The reason is that during longer downward movements, the lifting gear generates an excess of energy, which the running gear optimally consumes in the sense of recuperation by starting and stopping again several times, because starting up costs a particularly large amount of energy. Such a behavior is not only mechanically unfavorable, as it significantly increases

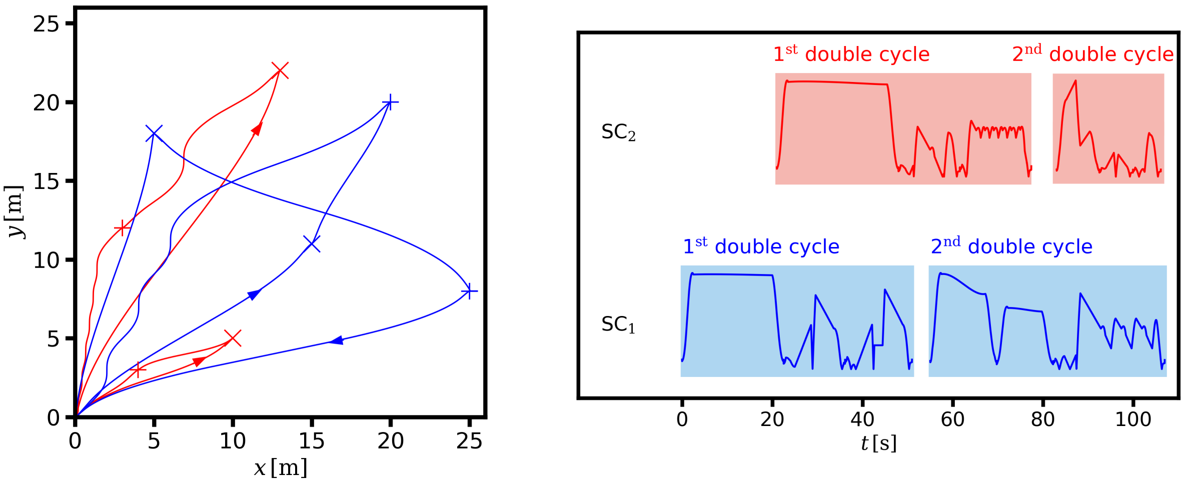


Figure 7: Optimized order planning of two stacker cranes with two double cycles for each one. Left panel: optimal pairing of storages (× marker) and retrievals (+ marker) with optimized trajectories, the arrows indicate the direction of travel, the colors distinguish the vehicles. Right panel: optimal schedule of the four double cycles as a result of (8,10-15) with the color code as in the left panel; the scaled resultant power profiles, i. e. the function $|P_{\mathrm{slow}}(t)+P_{\mathrm{fast}}(v,a)|$, are displayed in the colored rectangles; note that each double cycle consists of three travels.

material wear, but also from the electrical perspective, power fluctuations must be avoided. All in all, trajectories with optimized recuperation should be avoided on long descents and replaced with suitable alternatives. A simulation helps predictively to find such cases and to evaluate alternatives to them.

4 SUMMARY AND OUTLOOK

The presented simulation-based optimization framework enables an automated storage and retrieval scheduling for a number of stacker cranes in a high-bay warehouse. The overarching aim lies hereby in saving energy, where the foci of optimization are equally weighted. First, on a microscopic level a consequent trajectory optimization keeps as much as possible energy on one stacker crane by maximizing the recuperation between its two power trains. Second, on a macroscopic level optimized trajectories are combined to minimize the total energy consumption. Further electrical quantities can be evaluated to estimate the necessary dimension of circuit components as capacitors to detect potential power peaks and to save material. This seems all the more important because the cases of longer down travels with the movement behavior that is technically to be avoided must be detected in advance and suitable alternatives should be sought, simulated and evaluated.

Towards a more holistic warehouse management, a hybrid optimization would be highly desirable. Here, we have two improvements in mind: first, the trajectories are optimized not only considering one stacker crane but including the power trains of all stacker cranes. In more detail, let the index $i = 1 \ldots A$ distinguish the stacker cranes. The kinematic profiles of the two drives (the slow and the fast one) of each stacker crane are encoded via the velocities $v^{(1)}_{\mathrm{slow}}$, $v^{(1)}_{\mathrm{fast}}$ and the accelerations $a^{(1)}_{\mathrm{slow}}$, $a^{(1)}_{\mathrm{fast}}$, where P_{slow} and P_{fast} denote the repective power flow models. Analogously to Equation (5), the total recuperation summed over all stacker cranes is given by

$$\int_0^T \left| \sum_{i=1}^{A} P_{\mathrm{slow}}\left(v^{(i)}_{\mathrm{slow}}, a^{(i)}_{\mathrm{slow}}\right) + P_{\mathrm{fast}}\left(v^{(i)}_{\mathrm{fast}}, a^{(i)}_{\mathrm{fast}}\right) \right| \mathrm{d}t \tag{20}$$

After elaborating the details of such an extended approach, the necessary condition could be redeveloped. Second, intertwining the continuous and the combinatorial optimization would reflect the impact of the schedule on the shape of trajectories. One avenue in this direction points to an alternating iteration of scheduling and trajectory computation.

Both steps will contribute to achieve a higher level of self-consistency.

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