Proceedings of META'2018

7th International Conference on Metaheuristics and Nature Inspired computing

Sponsors

SYNERGY
Horizon 2020
GA No 692286

Table of contents

Unsupervised aerial image classification using fly algorithm and the Parisian approach, Maiza Mohammed [et al.] 1

Maturation of Individuals in Evolutionary Learning, Pavone Mario F. [et al.] 6

Multi Objective Optimization and Bionic Optimization Strategies in Engineering Design, Steinbuch Rolf 16

A Cuckoo Search Algorithm for the Flexible Ligand-Protein Docking problem, Khensous Ghania [et al.] 19

A Parallel Primal Heuristic to solve a Integrated Production Planning and Scheduling Problem, Menezes Gustavo [et al.] 22

WPBO: A New Metaheuristic Technique Inspired from Wolf Pack Behaviour, Toumi Abida [et al.] 31

A hybrid meta-heuristic-based multi-agent for Industry 4.0, Tetouani Samir 42

A constructive heuristic for two machine job shop scheduling problem under availability constraints on one machine, Benttaleb Mourad [et al.] 50

A heuristic rule for ranking scientific journals based on citation impact, Lando Tommaso [et al.] 53

Assessing Film Coefficients of Microchannel Heat Sinks, Cruz-Duarte Jorge Mario [et al.] 54

Advanced portfolio optimization problems, Tichy Tomas 62

A Matheuristic for the Rainbow Cycle Cover problem, Moreno Jorge [et al.] 63

Solving Multiple Sequence Alignment Problem Using a Discrete Hybrid Particle Swarm Optimization Algorithm., Deschênes Hugo [et al.] 70

Nature-inspired Deployment for Context-aware Services, Satoh Ichiro 73

New hybrid differential evolution algorithm for multiple objective optimization, Gagné Caroline [et al.] 83

On the Sensitivity of Grid-Based Parameter Adaptation Method, Tatsis Vasileios [et al.] 86

Application of fuzzy smoothing filter in empirical copula function, Kresta Ales 95

Machine-learning algorithms for portfolio optimization problems, Kouaissah Noureddine [et al.] 98

An Innovative Heuristic Mixed-Integer Optimization Approach for Multi-Criteria Optimization based Production Planning in the context of Production Smoothing, Kamhuber Felix [et al.] 101

New Approach for Continuous and Discrete Optimization: Optimization by Morphological Filters, Khelifa Chahinez [et al.] 110

A Combined Data Mining and Tabu Search approach for Single Customer Dial-a-Ride Problem, Morais Ana Catarina [et al.] 121

Fitting epidemiological models' parameters via multi-objective optimization, Ruiz Ferrández Miriam [et al.] 124

Iterated-Greedy-Based Metaheuristic with Tabu Search and Simulated Annealing for Solving Permutation Flow Shop Problem, Mesmar Khadija [et al.] 127

On VNS-GRASP and Iterated Greedy Metaheuristics for Solving Hybrid Flow Shop Scheduling Problem with Uniform Parallel Machines and Sequence Independent Setup Time, Aqil Said [et al.] 133

Dual tree wavelet transform based denoising of images using subband adaptive thresholding via genetic algorithm, Boukhobza Abdelkader [et al.] 148

A Bi-Objective Maintenance-Routing Problem; an efficient solving approach, Rahimi Mohammad [et al.] 155

Heat exchanger network synthesis with an enhanced superstructure and hybrid metaheuristics, Pavão Leandro [et al.] 158

Transformer's Health Index using Computational Intelligence, Alves Dos Santos Ramon [et al.] 165

Application of the surrogate models for protein structure prediction, Rakhshani Hojjat [et al.] 175

A Hybrid Genetic Algorithm for the job shop problem with transportation and blocking no wait constraints, Louaqad Saad [et al.] 178

A randomized search procedure combined with simulated annealing for the capacitated location routing problem, Ali Lemouari 188

Design and Parallel Implementation of the H264 application on Heterogeneous Architectures, Adda Chahrazed [et al.] 191

A Parallel Adaptive Differential Evolution Algorithm for Electric Motor Design, Essaid Mokhtar [et al.] 204

Virtual screening in electrostatic potential using an evolutionary algorithm, Puertas-Martín S. [et al.] 207

Improved NSGAII Based on a Multiple-Criteria Decision Analysis Method for Business Process Optimization, Mahammed Nadir [et al.] 210

Efficient Generic Support for Global Routing Constraints in Constraint-Based

Local Search Frameworks, Meurisse Quentin [et al.] 221

A New Hidden Markov Model Approach for Pheromone Level Exponent Adaptation in Ant Colony System, Bouzbita Safae 232

An algorithm based on dimensionality reduction through parameterized curves to solve a class of non-convex global optimization, Mohamed Rahal 241

Metaheuristics for Agent based Intelligent Evacuation System, Hajjem Manel [et al.] 244

Vector-Quantization Codebook Generation using LBG and Meta-Heuristic Algorithms, Boubechal Ikram [et al.] 247

Multi-gene genetic programming for feature selection in DNA Microarrays, Sfaksi Sara [et al.] 250

A modified cuckoo search algorithm for unsupervised satellite image classification, Kaouter Labed 253

Embedded System for Template Matching using Swarm Intelligence, De V. Cardoso Alexandre [et al.] 256

A parallel BSO metaheuristic for molecular docking problem, Saadi Hocine [et al.] 266

One-Class Subject Authentication using Feature Extraction by Grammatical Evolution on Accelerometer Data, Mauceri Stefano [et al.] 273

A heuristic approach for standalone clinical laboratory layout design, Faramarzi Oghani Sohrab [et al.] 283

Optimizing injection blow molding by neuroevolution, Silva Hugo [et al.] 291

Reducing environmental impacts in heat exchanger networks using Life Cycle Assessment and metaheuristic optimization techniques, Pavão Leandro [et al.] 301

Energy efficient scheduling of a multi-states and multi-speeds single machine system, Aghelinejad Mohsen [et al.] 309

Meta-heuristics for global reliability optimization of solder joints in electronic devices, Hamdani Hamid [et al.] 312

Dynamic Programming heuristic for k-means Clustering among a 2-dimensional Pareto Frontier, Dupin Nicolas [et al.] 314

The Evaluation-times Constrained Optimization (ECO) Problem and Its General Solver Model, Tamura Kenichi 322

A pickup and delivery problem with multi-trips, multi- ux, multi-vehicles and break placement, Noumbissi Tchoupo Moïse Aimé [et al.] 325

Iterated Local Search for the Integrated Single Item Lot Sizing Problem for a Flow Shop Configuration With Energy Constraints, Rodoplu Melek 328

Estimation-based algorithm for a stochastic one-commodity pick-up & delivery travelling salesman problem, Hadjadj Mohamed Seddik [et al.] 331

APM-MOEA : An asynchronous parallel model for multi-objective evolutionary algorithms, Mazière Florian [et al.] 339

Quaternion simulated annealing for large-scale unconstraint continuous optimization problems, El Afia Abdellatif [et al.] 351

A new cut-based genetic algorithm for graph partitioning applied to cell formation, Boulif Menouar 361

Optimization of an Underground Water Pipeline Building using Swarm Intelligence Algorithm PSO, Bellala Djamel [et al.] 370

A Genetic Algorithm for selecting feature extraction strategy and data mining algorithm to optimize GPCR classification, Bekhouche Safia [et al.] 374

A new domain decomposition method for a reaction advection diffusion equation, Mohamed Ridouan Amattouch 385

Planet Wars: an Approach Using Ant Colony Optimization, Baldominos Alejandro [et al.] 392

A Steganographic embedding scheme using Improved-PSO approach, Yamina Mohamed Ben Ali 399

Backpropagation and PSO-GA based Optimizations for a Neural Network Classification of Engine Fault Signals, Mjahed Soukaina [et al.] 407

Customer Order Scheduling by Scattered Wolf Packs, Riahi Vahid [et al.] 409

For solving the multi-depot fleet size and mix open vehicle routing problem, Ismail Sabrine [et al.] 419

Evolutionary operators in memetic algorithm for matrix tri-factorization problem, Hribar Rok [et al.] 426

IP Assignment Optimization for an Efficient NoC-based System using Multi-objective Differential Evolution, Bougherara Maamar [et al.] 435

A modified fixed point method for biochemical transport, Mohamed Ridouan Amattouch 445

Multi-objective optimization of the integrated problem of location assignment and straddle carrier scheduling in maritime container terminal at import, Dkhil Hamdi [et al.] 450

A hybrid algorithm based on Particle Swarm Optimization and Simulated Annealing for electrical power transmission, Zemzami Maria [et al.] 474

Modelling the shortest Hamiltonian circuit problem in superimposed graphs with Distributed Constraint Optimization Problems, Bouazzi Khaoula [et al.] 477

Optimization of Vehicle Routing Problem in the Context of Reverse Logistics of Handling Containers in Closed Loop, Bouanane Khaoula 481

Pricing & Lot Sizing problem in a hybrid manufacturing/ remanufacturing system with one-way substitution option, Zouadi Tarik [et al.] 483

Dynamic Simulated Annealing with Adaptive Neighborhood using Hidden Markov Model, Lalaoui Mohamed [et al.] 486

Fast Generation of Combinatorial Objects, Parque Victor [et al.] 496

Genetic Algorithms for Optimizing Nanostores' Routing in Emerging Markets, Sabiri Asmaa [et al.] 505

A cooperative multi-swarm particle swarm optimizer based hidden Markov model, Aoun Oussama [et al.] 509

Exact and multi-objective evolutionary-based approaches for process plan generation in a reconfigurable manufacturing environment, Touzout Fayçal A. [et al.] 521

A new heuristic method for a dynamic pricing and production problem, Couzon Paulin [et al.] 531

Haralick Texture Features Selection For Ultrasound Image Segmentation By Multigene Genetic Programming, Fatma Zohra Benabdallah [et al.] 534

An Energy-Efficient Permutation Flowshop Scheduling, örnek Mustafa Arslan 537

A Binary Genetic Algorithm for Solving Bi-Objective Multidimensional Knapsack Problem, Kabadurmuş özgür 548

An Agent-Based Label Propagation Algorithm for Community Detection, Fiscarelli Antonio Maria 558

Forecasting patients flow at an emergency department, Sadeghi Rezvan [et al.] 561

Single-objective Real-parameter Optimization:Enhanced LSHADE-SPACMA Algorithm, Hadi Anas [et al.] 564

Wifi emitters deployment for fingerprinting localization using genetic algorithm, Mourad-Chehade Farah [et al.] 574

Author Index **577**

first_page_proceedings.pdf **577**

An Innovative Heuristic Mixed-Integer Optimization Approach for Multi-Criteria Optimization based Production Planning in the context of Production Smoothing

Felix Kamhuber[1*], Thomas Sobottka[1], Peter Schieder[1], Maximilian Ulrich[1] and Wilfried Sihn[12]

1. Fraunhofer Austria Research GmbH, Theresianumgasse 27, Vienna 1040, Austria | Felix.Kamhuber@fraunhofer.at Thomas.Sobottka@fraunhofer.at | Peter.Schieder@fraunhofer.at | Maximilian.Ulrich@fraunhofer.at

2. Vienna University of Technology (TU Wien), Institute of Management Science, Theresianumgasse 27, Vienna 1040, Austria | Wilfried.Sihn@tuwien.ac.at

Abstract: This paper introduces an innovative heuristic mixed-integer optimization approach for multi-criteria optimization based production planning with rolling horizon for a discrete goods manufacturer. The fast moving consuming goods industry is characterized by standard and promotion sales volumes with different properties. State-of-the-Art multi-objective solution methods [1-3, 8-11] fail to address these properties adequately, due to the lack of considered subdimensions within a planning level. Furthermore these techniques contain static constraints rendering them unable to adapt the production system to seasonal (off-) peaks and to consider resource adjustments. In contrast, the presented approach features dynamic capacity-based restrictions and dynamic stock-levels within a given planning horizon. The product volumes per planning period (week) are split into two different subdimensions with specific constraints for order shifting and lot splitting for each subdimension and product. This approach pursues the optimized capacity utilization for a key production unit, featuring integer-based dynamic capacity restrictions. In addition to a smoothed production, mid-term stock-levels are simultaneously being optimized. The results show a 40% reduced output variation rate of the cost- and labor-intensive key equipment and a 30% reduced capacity requirement for downstream production equipment, compared with the initial manually compiled solution. Finally, the authors give an outlook on a possible enhancement of the method with statistical learning using periodic feedback from the production system.

Keywords: multi-product multi-period multi-objective production planning problem, heuristic optimization, lot splitting, production smoothing, rolling horizon, dynamic capacity constraints, dynamic stock-levels

1 Introduction

Modern production planning solutions are key enablers for today's highly competitive industrial environment. They (in-) directly influence the production system performance and profit of a factory. Different problem-specific heuristic [1, 5] and metaheuristic [2-3, 8-10] approaches characterized in [20] are proposed to meet the requirements of a *smoother* production. The latter ensures low flexibility costs and a good capacity utilization. An overview about practical and modelling issues as well as solution approaches concerning production smoothing problems presented in various contributions [1-5, 12, 19, 20] is given in section 3.

Trends in global and flexible markets, in combination with increasing product individualization, necessitate more flexible and responsive production systems [5, 7]. According to a Fraunhofer study [6], increasing variations in demand require sophisticated solutions concerning capacity flexibility measures, especially in the planning dimension week (47%).

This paper introduces an innovative heuristic optimization approach for a capacitated *Multi-Objective Multi-Product Multi-Period (MOMPMP)* production planning problem. The problem of scheduling the final production level is known as the *Production Smoothing problem* (PSP) [5].

This paper is structured as follows: After an introduction of the case study in section 2 and a literature review for the specific problem class at hand (see section 3), the developed heuristic optimization method is presented within section 4. A summary and discussion of the results in section 5 and an outlook on future research in section 6 conclude the paper.

* Corresponding author. Tel.: +43-676-888-61608; Fax: +43-1-504-6910-90. *E-mail address:* felix.kamhuber@fraunhofer.at

2 Case-study introduction and solution approach: An overview

This paper is centred on a case-study featuring an industrial European food producer aiming to introduce a smoother production flow to optimize the utilization of key production equipment/machines (see figure 1, production step 1). The key equipment represents a cost- and labor-intensive bottleneck unit within a soon-to-be-built factory. This production step influences other downstream production equipment within the total production system. The main task is the creation of an optimal, long-term (78 weeks in this use-case) dynamic capacitive-restricted production plan with a rolling horizon and the following optimization criteria:

goal (1) Reduced production volume peaks per planning period within the capacitive-restricted production system for all product types within a given planning horizon

goal (2) Optimized capacity utilization of a key production unit and downstream equipment

goal (3) Optimized stock levels for all product types and periods achieved and applied within a certain customer defined time frame

This specific optimization task should satisfy all relevant constraints concerning capacity, production process and product-type. In addition to reduced peaks in capacity demand through production smoothing, this heuristic optimization method enables a better capacity utilization resulting in a more energy-efficient production. It also prolongs the period until an investment in new capacity (i.e. machines) is necessary. Figure 1 provides a simplified process overview. An additional process step ('Extended maturing') was included as a buffer into the original process sequence to enable the operation of the production smoothing heuristic.

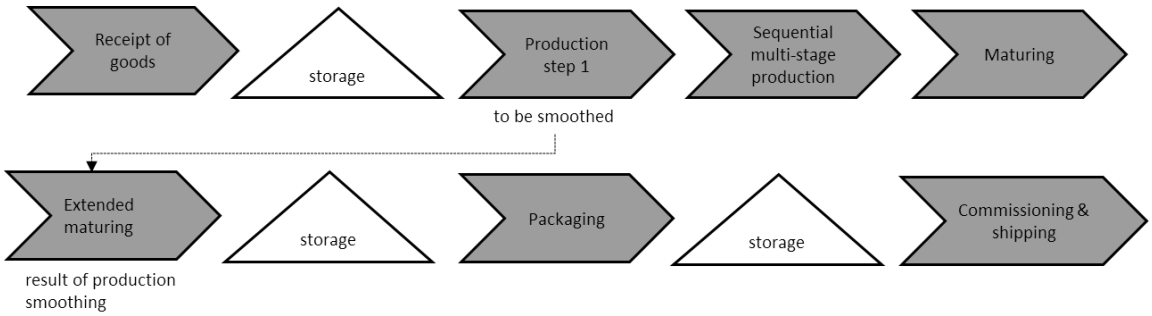

Figure 1: Production process system overview

The new factory has been planned using reliable forecasts for sales volume development to generate an initial production plan (→ initial solution). The heuristic has been originally applied with *goal (1)* and *goal* (2) to create the smoothed production volumes per period followed by a comprehensive discrete simulation study [17] to determine and validate the required capacities (→ production units) within the new production facility. Approaching the Go-Live of the plant in combination with the introduction of the rolling horizon the target function has been enhanced by *goal (3)* to further increase system productivity and process stability.

3 Literature review

Multi-objective multi-product multi-period (MOMPMP) production planning problems are NP-hard [1] and thus necessitate tailor-made, problem-specific (meta-) heuristics [20] to approximately solve problems of this complexity class within a reasonable time. The authors of [15, 19] give an overview of published literature dealing with MPMP models. Different multi-objective solution methods, including diverse mathematical models, are applied to deal with the complexity of purposeful search in the given solution space, namely:

- (MOGA) Multi-objective genetic algorithms [2, 8, 9, 12, 15]
- (Hybrid) Metaheuristics for (Mixed) Integer linear programming (MILP, ILP) models [3, 15, 16, 21]
- (MOPSO) Multi-objective particle swarm optimization [10], (MOBA) multi-obj. bat algorithm [18]
- Dynamic programming (DP) algorithms [5] and memory-based algorithms [11]
- Problem-specific heuristics [1, 5, 13] and rule-based algorithms [14]

In [5] the authors first present a dynamic programming algorithm for the exact solution of the corresponding production smoothing problem requiring significant computational effort, rendering its use impractical in a given real world environment. Thus, a 2-phase-metaheuristic approach is proposed – the problem is split into a constrained *batching problem* (BP) and *sequencing problem*. This approach offers some similarities with the proposed method in this paper, because jobs are split into smaller batches that can be consolidated with batches in other periods of the same product type. The main difference and shortcoming of existing (meta-) heuristics is the missing utilization of subdimensions within a certain planning dimension. Furthermore, the proposed rolling horizon approach considers dynamic capacity and dynamic target stock-level bounds, thus enabling the consideration of seasonal effects and resource (labor, production equipment) adjustments. The result evaluation is performed with an *index (1)* performing a weighted comparison of each part-goal result value.

4 Developed heuristic optimization method

The presented heuristic mixed-integer approach is modular and consists of five sequential optimization phases. The target function $f(\mathrm{x})$ including its three defined part-goals calculates a weighted and normalized fitness-value, the « multi-criteria smoothing index » (MCSMI). This target function includes an evaluation function for a smoothed production planning horizon (f_1), next to an evaluation for optimized stock-levels (f_2) and an evaluation function to measure the smoothed capacity utilization (f_3):

$$\boldsymbol{Minimize}\ f(x) = \omega_1 \sum_{\substack{i=1\\j=1}}^{\substack{i=n\\j=m}} f_1(k\_prod_{ij}) + \omega_2 \sum_{\substack{i=1\\j=1}}^{\substack{i=n\\j=m}} f_2(k\_stock_{ij}) + \omega_3 \sum_{\substack{i=1\\c=1}}^{\substack{i=n\\c=o}} f_3(k\_capacity_{ic}) + \omega_4 \sum_{i=1}^{i=n} f_4(k\_plant_i)\,, \tag{1}$$

$$\boldsymbol{Subject\ to} \sum_{j=1}^{m} q_{ij} \le q_{max_i}, \forall i, \tag{2}$$

$$q_{ij} \in A_i, q_{max_i} \in A_i, \tag{3}$$

$$delta\_q_{prod_{ij}} \le delta_{max}, \forall delta_{q_{prod_{ij}}}, \tag{4}$$

$$delta_{Max} \in A_i \tag{5}$$

Legend:

ω_1 - ω_4 ... $part - goal\ weights$
m ... $total\ number\ of\ product\ types$
n ... $total\ number\ of\ periods\ within\ the\ planning\ horizon$
o ... $total\ number\ of\ capacity - units\ within\ the\ planning\ horizon$
f_1 ... $evaluation\ function\ for\ article\ production\ gradient\ (based\ on\ product\ type\ and\ planning\ period)$
f_2 ... $evaluation\ function\ for\ stock - level\ gradient\ (based\ on\ product\ type\ and\ planning\ period)$
f_3 ... $evaluation\ function\ for\ capacity - utilization\ gradient\ (based\ on\ capacity\ unit, planning\ period\ and\ amount\ of\ utilization)$
f_4 ... $evaluation\ function\ for\ plant\ production\ gradient\ (based\ on\ cumulated\ product\ type\ production\ gradient\ per\ planning\ period)$
k_prod_{ij} ... $production\ gradient\ for\ product\ type\ j\ in\ period\ i$
k_stock_{ij} ... $stock - level\ gradient\ for\ product\ type\ j\ in\ period\ i$
$k\_capacity_{ic}$ ... $capacity - level\ gradient\ for\ period\ i\ on\ capacity\ c$
k_plant_i ... $plant\ production\ gradient\ for\ cumulated\ sum\ of\ article\ production\ gradient\ in\ period\ i$
q_{ij} ... *production (share) quantity of product type j in period i*
slq_{ij} ... *stock-level quantity of product type j in period i*
$target_{slq_{ij}}$ ...*dynamic target stock-level quantity of product type j in period i*
cul_{ic} ... *capacity-unit level in period i on capacity c*
q_{max_i} ... *capacity constraint: max. allowed production quantity in period i*
$delta\_q_{prod_{ij}}$ ... *offset quantity of product type j in period i*
$delta_{max}$ ... *integer constraint for max. allowed offset [in periods]*
A_i ... $set\ of\ acceptable\ values\ for\ q_{ij}, q_{max_i}, delta\_q_{prod_{ij}}, delta_{Max}$

The defined part-goal functions $f_1 - f_4$ are represented by gradients provided in the following format:

$$f_1(k\_prod_{ij}) = Abs|q_{i+1,j} - q_{ij}| \tag{6}$$

$$f_2(k\_stock_{ij}) = Abs|slq_{ij} - target\_slq_{ij}| \tag{7}$$

$$f_3(k\_capacity_{ic}) = Abs|cul_{i+1,c} - cul_{ic}| \tag{8}$$

$$f_4(k\_plant_i) = \sum_{j=1}^{j=m} Abs|q_{i+1,j} - q_{ij}| \tag{9}$$

A gradient function, f_1 for instance, is calculated from (absolute) changes in production volumes between adjacent time periods. When compared with relative gradients, absolute gradients are preferred for evaluation because they penalize large deviations much stronger, and relative gradients could distract the algorithm from its goal. The decision maker's preferences are represented by the weights (equally set to 1 by default).

The given periodic-dynamic production capacity constraint (2) is a hard constraint and must strictly be fulfilled in each period to generate a valid convertible solution. Constraint (3) specifies that A_i, a set of specific multiples of certain integer values, according to an A/B/C categorization, is allowed for production only (see table 1, with « 1 » as the smallest possible batch unit of a product type).

Table 1 : Acceptable multiples for (q_{ij}, q_{max_i}) according their article specific ABC value

Parameters / Multiples of ABC value	A	B	C
q_{ij}, q_{max_i}	6	3 || 6	1

Constraints (4) and (5) specify that the applied article-specific offsets for shifted production volumes must be lower than the maximum allowed offset values from the master data (→ technological requirement). There are two given maximum *integer* (→ planning periods) offset values per product type, one for standard sales volumes and one for promotion sales volumes. Table 2 lists the core functional requirements and constraints.

Table 2: Functional requirements for the optimization modules

Module, title and evaluation function	Description and constraints
Module 1: Production smoothing of promotion sales volumes (f_1)	This module reduces peak volumes of promotion-sales for each product and period according to flexible restrictions determined by product type, planning period, capacity and A/B/C (→ formulas (6) & (9)) category.
Module 2: Production smoothing of standard sales volumes (f_1)	This module reduces standard peak volumes for each product and period, according to flexible restrictions determined by product type, planning period, capacity and A/B/C (→ formulas (6) & (9)) category.
Module 3: Stock-Level smoothing (f_2)	This module optimizes defined mid-term stock-levels (see figure 3) in order to comply with target stock-levels according to formula (7).
Module 4: Capacity utilization forecast calculation (f_3)	This module calculates the capacity utilization forecast. This forecast is evaluated according to formula (8).

The multi-objective MPMP algorithm (see Algorithm 1), consists of five phases, which manipulate the production program towards different part-goals that are summed up in cost function $f(x)$.

Phase 1: Processing of master data, current production and demand plan (rolling horizon → each period)
Phase 2a: Minimization of promotion sales volumes peaks in the production plan. This phase of the algorithm calculates an average weekly production load (→ calculated from cumulated (→ C-articles) or article-specific (→ A/B articles) standard production volumes) and tries to shift shares of specific promotion volumes, which are above the average production load, into weeks that are below the average production load (gaps), as visualized in figure 2. These gaps are filled up according to the following heuristic:

(1) The gaps in periods closest to the current period are filled up first, until the current «*average production load*» *(APL)* per period is achieved (see Algorithm 1, rows 15 – 29)

(2) The remaining quantities are shared between all offset-periods, resulting in a higher *APL*

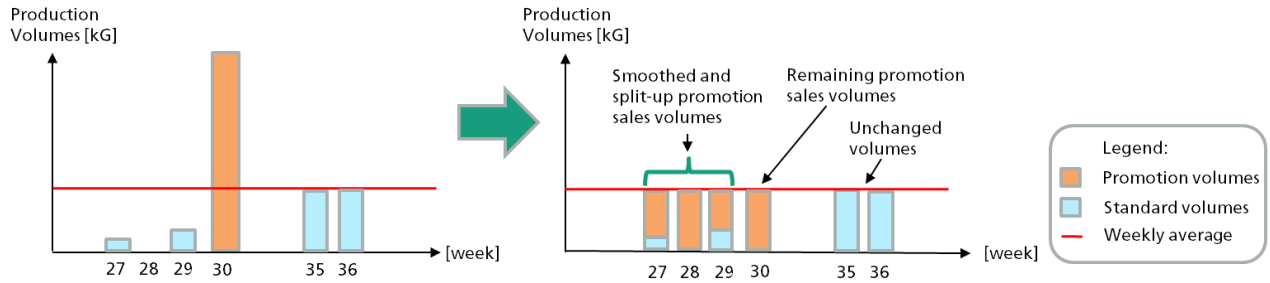

Figure 2: Promotion sales volumes smoothing (example)

The shifting of production volumes (promotion, standard) takes into account maximum offset intervals *(4)*. In addition shifting is only possible into earlier production weeks (due to the structure of the input data) in order to still meet the production deadlines. Within the preparation phase, the input sales volumes have to be checked and accumulated to calculate product-specific gradients for production, capacity and stock-levels.

Phase 2b: Standard volume smoothing uses the same approach as phase 2a. An average production load (→ calculated from both standard and smoothed promotion volumes after phase 2a) is determined and standard production volumes that are above this derived average production load are preferably shifted to weeks that are below the considered average according to the heuristic in phase 2a.

Phase 2a and 2b feature some tweaks, e.g. a floating re-calculation of the average production load value. Another performance gain results from using smoothing indices for each phase, ensuring that an over-control is avoided by allowing a small percentage value to remain above the average production load value. This tweak further reduces the amount of production volume that needs to be shifted significantly. Optimization tests have shown this factor to be around 7-10%, depending on the specific dataset received.

Phase 3 - 4: Within these phases the filling level of each carrier-unit (rack) for the products, is evaluated and optimized according to its specific capacity utilisation and under the production restrictions (2) – (5). According to these restrictions, production volumes have to be a multiple of the minimum production volume of a product and are rounded tactically to half or full racks for each product in each period, according to the corresponding A/B/C-category of each product (see table 1). Depending on the stock level, rounding attempts to reach the optimal stock level, either by rounding up or down (or commercial) to increase, decrease or keep a certain stock level.

Phase 5: Smoothing via stock-level strategies is used (in addition to the stock level optimization of phase 3 - 4) to keep stock levels from a certain (shorter than in phase 3 - 4)) time frame close to the defined target stock level. This is done by calculating an average expected stock level over a certain number of weeks (adjustable, an example for this is « lead time 2 » in figure 3) and adding/removing the difference between the calculated stock level and the preferred stock level to/from the production plan (see the green dashed line in figure 3). Adding or removing production volumes is performed considering the average production volume while trying to maintain a smoothed production plan. Figure 3 shows a typical stock-level trend of a product (lead time = 12 weeks; given S_{min} , S_{max}). The goal is to improve the stock-level of the the influenceable time-period only, and not of the full planning horizon, since this would not be beneficial. This results in a short phase 5 with steep improvements of the objective function value realized within a longer time-span (see figures 3 – 4).

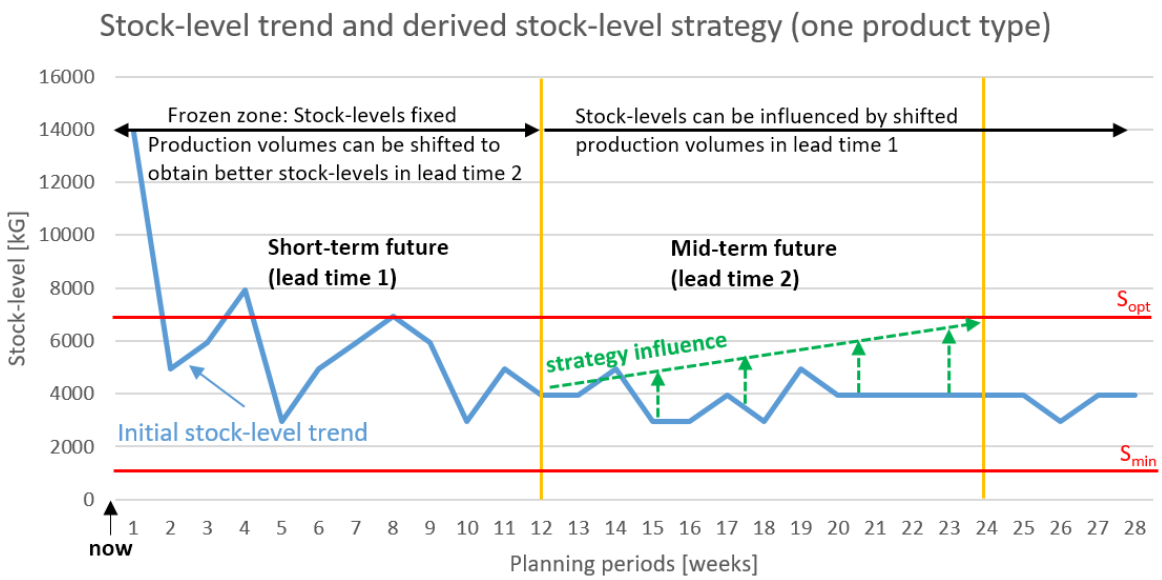

Figure 3: Stock-level strategies based on the specific stock-levels in the mid-term future

The final result is a multi-objective smoothed production plan for all products and the full planning horizon. It considers the planning dimensions «production volumes», split into the promotion and standard sales volumes dimension, next to the planning dimensions «stock-levels» and «capacity utilization».

Algorithm 1: The Multi-Objective MPMP Production Smoothing Heuristic

```
Begin // process current master data, production and demand plan (rolling horizon → each period)
Calculate production plan solution matrix ppsm(m,n) // matrix with m (products) rows and n (periods) columns
Calculate stock-level gradient matrix slgm(m,n) // matrix with m rows and n columns
Calculate capacity utilization forecast matrix cufm(m,o) // matrix with m rows and o (capacity types) columns
f(x) ⟵ Evaluate (ppsm, slgm, cufm)
m' ⟵ m (derive prio-list m')    // priorisation by ABC analysis based on yearly average volumes and marginal returns
Update ppsm' ⟵ ppsm; sglm' ⟵ sglm  // update production and stock-level matrices
(ppsm0', ppsm1') ⟵ split ppsm' // performs split into two matrices : for standard (0) and promotion (1) sales volumes
For j = 1 to m
    For i = n to 1  // starting with the last period iterating to the first
        Calculate mj ⟵ mean(j, n/3)  // floating mean value valid for product j for n/3)periods
        If (i = n) Then y ⟵ ppsm1'(i,j) // derive production promotion amount for product j in period i
        Else y ⟵ ppsm1''(i,j)
        End If
        delta ⟵ compare (y − mj)
        If (delta > 0) Then
            If (j ϵ(A||B)) Then  // if product type equals (A || B), stores week indices/quantities
                                 // in bwl HashMap, considering capacity and article constraints
                bwl ⟵ search best local weeks including their quantities
                checkCapacityAndArticleConstraints (ppsm', bwl)
                Update ppsm1'' ⟵ ppsm1'(bwl)  // update ppsm1' by using bwl
            Else    // stores week indices/quantities in bwg HashMap incl. capacity/art. constraints
                bwg ⟵ search best global weeks including their quantities
                checkCapacityAndArticleConstraints(ppsm', bwg)
                Update ppsm1'' ⟵ ppsm1'(bwg) // update ppsm1' by using bwg
            End If
            Update cufm' ⟵ cufm // capacity-utilization forecast update
            Update ppsm'' ⟵ (ppsm0', ppsm1''); f(x) ⟵ Evaluate (ppsm'', slgm, cufm')
        End If
    End For // next period for this article
End for // next article from prio-list m'
Repeat 2b ⟵ (2a) : Update ppsm0''  ⟵ ppsm0' // repeat steps of (2a) for (2b) with ppsm0' instead of ppsm1'
    If (Update ( ppsm0'' ⟵ ppsm0'(bwg ||bwl) Then
        Update sglm'' ⟵ sglm'  // actualise stock-level matrix (standard volumes!) each iteration
    // Update ppsm''' ⟵ (ppsm0'', ppsm1'') instead of ppsm'' ⟵ (ppsm0', ppsm1'');
// Update cufm'' ⟵ cufm'; instead of cufm' ⟵ cufm; → Evaluate (ppsm''', slgm'', cufm'')
    End if
// capacity utilization forecast finished → start rack-optimization
For j = 1 to m
    For i = 1 to n
    Round (ppsm''' ⟵ ppsm(i,j)''') // round tactically to half ||full racks for each product in
                                   // each period according to // A/B/C depending on stock levels
    // → according to target function part f2(x) : roundings support to better achieve optimal stock-levels
    Update (sglm''' ⟵ sglm(i,j)''); Update (cufm''' ⟵ cufm''); f(x) ⟵ Evaluate (ppsm''')
    End For
End For
// Phase 3 – 4 finished  → perform mid-term stock-level strategies for all products and certain time frames
For j = 1 to m
    Derive optStockLevel (osl); minStockLevel (msl); leadTime (lT) ⟵ master data matrix (mdm)
    Initialize delta_stock ⟵ 0
    For i = lT to 2 * lT // definition to perform changes in leadTime «1 » based on stockLevel in leadTime « 2 »
        Calculate/Update delta_stock ⟵ Compare Abs(osl − actualStockLevel(i,j))
    End For
    If (delta_stock < msl) Then
        bwl ⟵ search best local weeks including their quantities to fill 1st local / 2nd global stock-level gaps
        checkCapacityAndArticleConstraints(ppsm''', bwl)
    Else If (delta_stock > osl * toleranceFactor) Then
        bwl ⟵ search best (a) local/ (b) global weeks incl. their quantities to downlevel current stock-level
    End If
    For i = 1 to lT  // perform production changes «fast » within 1st lead time
        While (bwl !isEmpty()) Do
            Update ppsm'''' ⟵ ppsm0(i,j)'''(bwl) // update ppsm by using bwl on ippsm0'''
            Update (sglm'''' ⟵ sglm(i,j)''') ; Update (cufm'''' ⟵ cufm''') ;
            f(x) ⟵ Evaluate (ppsm'''')
        End While
    End For
End For
Return (ippsm''''; isglm''''; icufm'''') // print final optimized multi-criteria solution; End
```

Phase 1: Preparation

Phase 2a: promotion volume smoothing

Phase 2b: standard volume smoothing

Phase 3 - 4 : rack optimization

Phase 5 : stock-level strategies

5 Optimization results

The optimization results presented were obtained by a given real-life scenario with a specific dataset (78 planning weeks: 13/2018 – 38/2019) and the default settings of the algorithm.

The 2nd optimization phase, representing the core-unit (three of four part-goals are improved) of the proposed multi-phase heuristic approach, includes the production smoothing steps for promotion and standard volumes and accounts for 25% of global goal optimization. The third step is mandatory for the final rack preparation. However, it does not improve the global goal. The fourth optimization step raises or reduces stock-levels in order to create full racks and to simultaneously pursue the target stock level for each product in each period (fig. 5). Achieving filled racks maximizes the capacity utilization of the racks. The 5th optimization phase tries to shift production volumes in the near future to achieve optimal stock-values in the mid-term figure (fig. 2).

Figure 4 features the global goal optimization results (represented as trend), while figure 5 shows the individual part goal results. Figure 5 shows that the total capacity gradient (aggregated by 5 sub-capacity gradients itself) is affected by the optimization of the production gradient in phase 2. The production and capacity gradient optimization within phase 2 is derived at the cost of a worse stock-level gradient.

These results are achieved by shifting only ~ 8 – 10% of the annual production volume. However, the smoothing requires (1) lots to be split into part lots (→ shifting of part lots into existing other lots physically only leads in total to 5 – 7% more lots) and (2) additional (simple conditioning) storage capacity (fig. 1). These conditions result in additional – compared with the savings considerably lower – investment and setup costs.

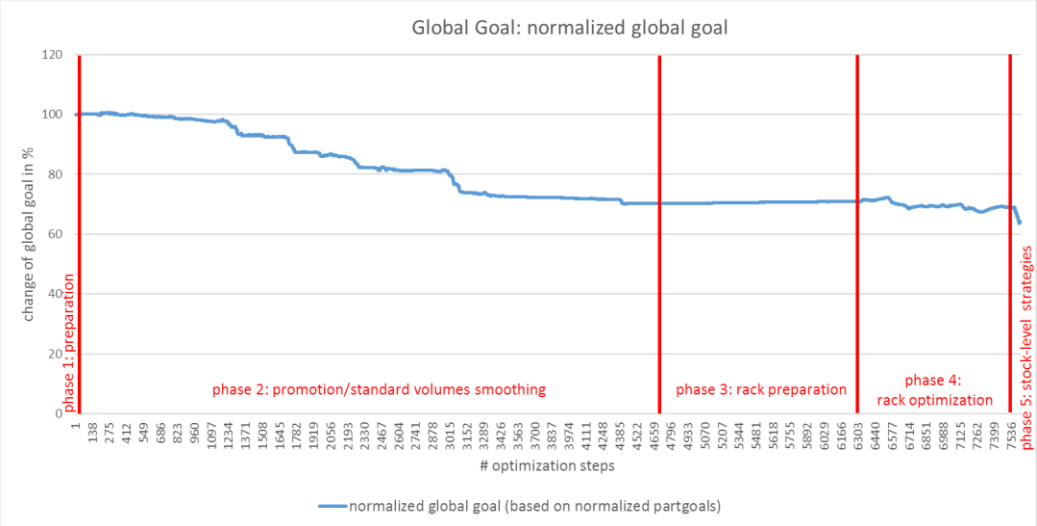

Figure 4: Global goal optimization

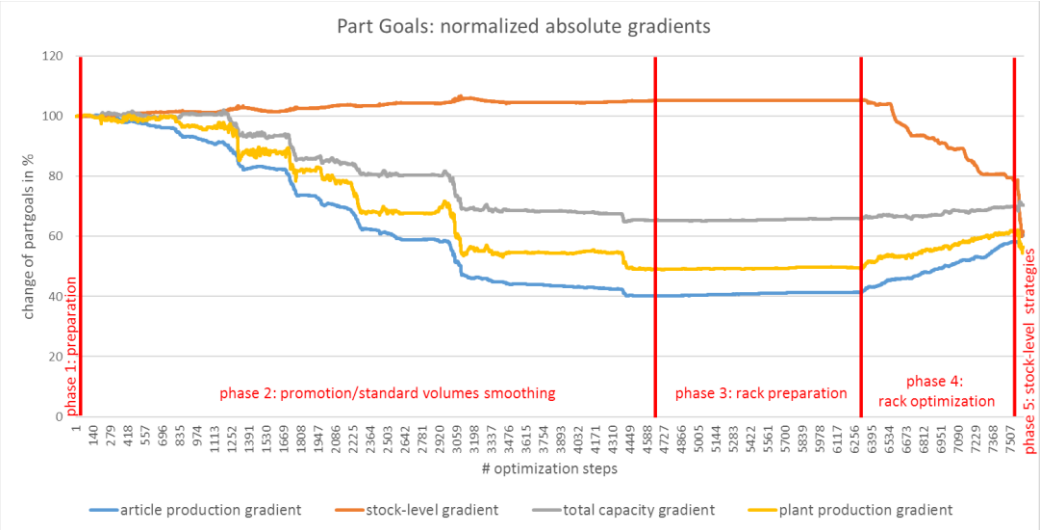

Figure 5: Individual part-goal optimization

6 Outlook and conclusion

The global goal optimization results release – compared with the initial production plan – a production smoothing potential of approximately 30%. Despite the fact that the absolute stock-level gradient cannot be measured explicitly in terms of minimized costs, the total cost saving potential from the production and capacity gradient is around 30%. This results in significantly lower investments for the new factory (fewer production units necessary) and 40% reduced operation costs on the key equipment (→ reduced labour costs achieved with balanced operation times) compared with – in comparison – very low additional costs for the additional process step. The actual optimization potential varies slightly with the specific planning scenario. Additionally, the method promises to be scalable as it becomes more effective with increasing appearance of peaks – and according to forecasts, more peaks are indeed to be expected in the future. Furthermore, this method enables an around 30% more uniform capacity utilization, resulting in a more energy-efficient production (because fewer units are in operation at a certain moment) and a longer lasting production facility configuration before the next expansion stage becomes necessary.

Future work on this method include a dedicated optimization of the capacity utilization – that is currently only implicitly optimized (see fig. 5), and an additional smoothing of packaging processes downstream of the hitherto considered production steps. Another important issue is – besides the comparison of this heuristic optimization method with a metaheuristic approach – to evaluate the influence of production as well as environmental conditions on the production plants' energy consumption. Therefore, after the collection of energy and production data, which is currently under way, the collected data will be analysed in order to find feasible opportunities - e.g. correlations between the production plan and the energy consumption. Thus, energy consumption will be integrated as an explicit optimization feature into the algorithm.

Another line of follow-up research is the algorithm-based analysis of collected production data, in order to better and automatically adjust the article specific constraints and stock-level strategies in the future. This learning from historic production data will lead to the algorithm becoming adaptive, thus unlocking further optimization potential currently inaccessible due to the fixed parameters, constraints and strategies.

7 Acknowledgements

This work is part of the research project ASPeCT, funded by the Austrian Research Promotion Agency (FFG) (Project number 858655). The authors would like to thank all project partners for their contributions.

References

[1] M. Karimi-Nasab, I. Konstantaras. A random search heuristic for a multi-objective production planning. *Computers & Industrial Engineering* (2012) 479--490.

[2] M. Karimi-Nasab, M. B. Aryanezhad. A multi-objective production smoothing model with compressible operating times. *Applied Mathematical Modelling* (2011) 35, 3596–3610.

[3] M. S. Al-Ashhab. An Optimization Model for Multi-period Multi-Product Multi-objective Production Planning, *International Journal of Engineering & Technology* (2016), IJET-IJENS Vol:16 No:01

[4] M. Yavuz, E. Akçali. Mesut Yavuz & Elif Akçali. Production smoothing in just-in-time manufacturing systems: a review of the models and solution approaches, *International Journal of Production Research* (2007), 45:16, 3579-3597.

[5] M. Yavuz, E. Akçali, S.Tüfekçi. Optimizing production smoothing decisions via batch selection for mixed-model just-in-time manufacturing systems with arbitrary setup and processing times, *International Journal of Production Research, 44*:15 (2006), 3061 – 3081.

[6] D. Spath, O. Ganschar, S. Gerlach, M. Hämmerle, T. Krause, S. Schlund. Produktionsarbeit der Zukunft - Industrie 4.0. Fraunhofer-Institut für Arbeitswirtschaft und Organisation IAO, Stuttgart (2013), ISBN 978-3-8396-0570-7.

[7] C. Morawetz. Vorgehensmodell zur Entwicklung eines Entscheidungsunterstützungssystems zur kostenoptimalen mittelfristigen Kapazitätsanpassung, doctoral thesis, Vienna University of Technology (2015).

[8] M. M. Soares, G.E. Vieira. A new multi-objective optimization method for master production scheduling problems based on genetic algorithm, Int. J. Adv. Manuf. Technol. 41 (2009), 549-567.

[9] N. Chakraborti, B.S. Kumar, V.S. Babu, S. Moitra, A. Mukhopadhyay. A new multi-objective genetic algorithm applied to hot-rolling process, Appl. Math. Model. 32 (2008) 1781 – 1789.

[10] D. Y. Sha, H.H. Lin. A multi-objective PSO for job-shop scheduling problems, Expert Systems with Applications, 37:2 (2010) 1065 – 1070.

[11] A. Cheriet, F.Cherif. Solving dynamic multi-objective problems using a copula-based estimation of distribution algorithm, *Proceedings of 6th META* (2016) 78 – 80.

[12] O. Masmoudi, A.Yalaoui, Y.Ouazene, H.Chehade. Simultaneous lot-sizing and scheduling in a flow-shop system with energy consideration, *Proceedings of 6th META* (2016) 349 – 351.

[13] M. Karimi-Nasab, S.M.T. Fatemi Ghomi. Multi-objective production scheduling with controllable processing times and sequence-dependent setups for deteriorating items, *International Journal of Production Research*, 50:24 (2012), 7378 – 7400.

[14] Y. Monden. Toyota production system: An Integrated Approach to Just-In-Time. Taylor Francis Group, 4th edition (2012), ISBN 978-1-4398-2097-1.

[15] I. Saracoglu, S. Topaloglu, T. Keskinturk. A genetic algorithm approach for multi-product multi-period continuous review inventory models, Expert Systems with Applications 41 (2014), 8189 – 8202

[16] S.Torkaman, S.M.T Fatemi Ghomi, B.Karimi. Multi-stage multi-product multi-period production planning with sequence dependent setups in closed-loop supply chain, Computers & Industrial Engineering 113 (2017) 602-613.

[17] T. Sobottka, F. Kamhuber, J. Henjes, W. Sihn. A case study for simulation and optimization based planning of production and logistics systems, Proceedings of the 2017 Winter Simulation Conference.

[18] A.E. Samrout, O. Braydi, R. Younes, F. Trouchou, P. Lafon. A new hybrid method to solve the multi-objective optimization problem for a composite hat-stiffened panel, *Proceedings of 6th META* (2016), 116 – 124.

[19] Z. Sazvar, S.M.J. Mirzapour Al-e-hashem, K. Govindan, B. Bahli. A novel mathematical model for a multi-period, multi-product optimal ordering problem considering expiry dates in a FEFO system, Transportation Research Part E: Logistics and Transportation Review, Volume 93 (2016), 232- 261.

[20] F. Ansari, K. Schenkelberg, U. Seidenberg & M. Fathi. Problem Solving in the Digital World: Synoptic Formalism, Incrementalism and Heuristics, Encyclopedia of Computer Science and Technology, 2nd Edition; Laplante, P., Ed.; Taylor & Francis: New York (2017).

[21] Talbi, EG. Annals of Operations Research (2016) Volume 240, 171-215, https://doi.org/10.1007/s10479-015-2034-y

Author Index

örnek Mustafa Arslan, 537–547
šilc Jurij, 426–434

Abdelmalik Taleb-Ahmed, 148–154
Abdennacer Bounoua, 148–154
Abderrahim Belmadani, 110–120
Abdul Sattar, 409–418
Adda Chahrazed, 191–203
Aghelinejad Mohsen, 309–311
Ali Lemouari, 188–190
Allali Karam, 127–147
Alves Dos Santos Ramon, 165–174
Amaya-Contreras Iván Mauricio, 54–61
Amodeo Lionel, 325–327
Aoun Oussama, 509–520
Aqil Said, 127–147
Arbaoui Taha, 561–563, 574–576

Baldominos Alejandro, 392–398
Bekhouche Safia, 374–384
Bellala Djamel, 370–373
Benboudjelthia Hafida, 266–272
Bennouar Djamel, 435–444
Benslimane Sidi Mohamed, 210–220
Benttaleb Mourad, 50–52
Benyamina Abou Elhassen, 191–203
Benyettou Mohamed, 2–5
Benyoucef Lyes, 521–530
Benzid Redha, 247–249
Bertoli-Barsotti Lucio, 53
Betka Abir, 31–41
Bouamama Sadok, 477–480
Bouanane Khaoula, 481, 482
Bouazzi Khaoula, 477–480
Boubechal Ikram, 247–249
Bougherara Maamar, 435–444
Boukhobza Abdelkader, 148–154
Boulif Menouar, 361–369
Bouzaachane Khadija, 407, 408
Bouzbita Safae, 232–240
Bouziri Hend, 244–246
Brevilliers Mathieu, 175–177, 204–206
Bue Martin, 283–290

Calenda Tobia, 6–15
Cardoso Pedro, 121–123
Chabchoub Habib, 419–425, 450–473
Chehade Hicham, 561–563, 574–576
Cherif Chahira, 2–5
Chouarfia Abdallah, 19–21
Correa Cely Carlos Rodrigo, 54–61
Couzon Paulin, 531–533
Cruz-Duarte Jorge Mario, 54–61
Cutello Vincenzo, 6–15

Dahane Mohammed, 521–530
De Landtsheer Renaud, 221–231
De Macedo Mourelle Luiza, 165–174, 256–265, 435–444
De V. Cardoso Alexandre, 256–265
Delisle Pierre, 339–350
Denysiuk Roman, 291–300
Deschênes Hugo, 70–72
Di Stefano Antonino, 6–15
Djerou Leila, 250–252
Dkhil Hamdi, 450–473
Duarte Fernando, 291–300
Dupin Nicolas, 314–321

El Afia Abdellatif, 351–360
El Hadaj Salah, 407, 408
El Hami Abdelkhalek, 312, 313
Elafia Abdellatif, 486–495, 509–520
Elhami Norelislam, 474–476
Essaid Mokhtar, 204–206

Fahsi Mahmoud, 210–220
Faramarzi Oghani Sohrab, 283–290
Fatma Zohra Benabdallah, 534–536
Fernades Hortênsio, 121–123
Fiscarelli Antonio Maria, 558–560
Flori Pauline, 325–327
Foderean Daniel, 204–206
Fournier Mathieu, 83–85
Frota Yuri, 63–69

Gagné Caroline, 70–72, 83–85, 339–350
Galvão Dias Teresa, 121–123
Garcia-Perez Arturo, 54–61
Gaspar-Cunha António, 291–300
González-Evstrópova María, 392–398
Gravel Marc, 83–85

Haddou Benderbal Hichem, 521–530
Hadi Anas, 564–573
Hadjadj Mohamed Seddik, 331–338

Hajjem Manel, 244–246
Hamdani Hamid, 312, 313
Hammami Moez, 477–480
Hmina Nabil, 474–476
Hnaien Faicel, 50–52
Hribar Rok, 426–434

Idoumghar Lhassane, 175–177, 204–206
Iguider Adil, 178–187
Ismail Sabrine, 419–425
Itmi Mhamed, 474–476
Ivorra Benjamin, 124–126

Jambi Kamal, 564–573

Kabadurmuş özgür, 548–557
Kalla Hamoudi, 370–373
Kamach Oulaid, 178–187
Kamhuber Felix, 101–109
Kaouter Labed, 253–255
Kemcha Rebiha, 435–444
Kheddouci Hamamache, 331–338
Khelifa Chahinez, 110–120
Khensous Ghania, 19–21
Kouaissah Noureddine, 98–100
Krajecki Michaël, 339–350
Kresta Ales, 95–97

L. Redondo J., 207–209
López Redondo Juana, 124–126
Lahyani Rahma, 419–425
Lalaoui Mohamed, 351–360, 486–495
Lando Tommaso, 53
Leila Djerou, 534–536
Lepagnot Julien, 175–177
Lepagnpt Julien, 204–206
Louaqad Saad, 178–187

M. Ortigosa P., 207–209
Mahammed Nadir, 210–220
Maiza Mohammed, 2–5
Martínez Ortigosa Pilar, 124–126
Martin Emilio, 392–398
Martins Simone, 63–69
Mateus Geraldo, 22–30
Mauceri Stefano, 273–282
Mazière Florian, 339–350
Mcdermott James, 273–282
Mehdi Malika, 266–272
Mellouli Khaled, 244–246
Menezes Gustavo, 22–30
Mesmar Khadija, 127–132
Messabih Belhadri, 19–21
Meurisse Quentin, 221–231
Miyashita Tomoyuki, 496–504
Mjahed Soukaina, 407, 408
Mohamed Ali, 564–573
Mohamed Ben Ali Yamina, 374–384
Mohamed Rahal, 241–243
Mohamed Reghioui, 483–485
Mohamed Ridouan Amattouch, 385–391, 445–449
Morais Ana Catarina, 121–123
Moreno Jorge, 63–69
Mourad-Chehade Farah, 574–576
Moussaoui Manel, 250–252

Nedjah Nadia, 165–174, 256–265, 435–444
Newton M A Hakim, 409–418
Nielsen Frank, 314–321
Nouali Taboudjemat Nadia, 266–272
Noumbissi Tchoupo Moïse Aimé, 325–327

Oesterle Jonathan, 561–563
Ortobelli Sergio, 98–100
Ouazene Yassine, 309–311, 531–533
Ouldkradda Ali, 210–220
Ourlis Lazhar, 370–373
Ousmer Sabrine, 266–272

Pérez-Sánchez H., 207–209
Papa Gregor, 426–434
Parque Victor, 496–504
Parsopoulos Konstantinos, 86–94
Pavão Leandro, 158–164, 301–308
Pavone Mario F., 6–15
Petelin Gašper, 426–434
Pinto Rene, 291–300
Polash M M A, 409–418
Ponsard Christophe, 221–231
Puertas-Martín S., 207–209

Radi Bouchaïb, 312, 313
Raghay Said, 407, 408
Rahimi Mohammad, 155–157
Rakhshani Hojjat, 175–177
Ramos ángel, 124–126
Ravagnani Mauro, 158–164, 301–308
Riahi Vahid, 409–418
Riane Fouad, 505–508
Rodoplu Melek, 328–330
Ruiz Ferrández Miriam, 124–126

Saadi Hocine, 266–272
Sabiri Asmaa, 505–508
Sadeghi Rezvan, 561–563

Saez Yago, 392–398
Santos Lucas, 22–30
Sarubbi João, 22–30
Satoh Ichiro, 73–82
Sbaa Salim, 31–41
Schieder Peter, 101–109
Seghir Rachid, 247–249
Selmi Aymen Takie Eddine, 250–252
Sfaksi Sara, 250–252
Sihn Wilfried, 101–109
Silva Hugo, 291–300
Sioud Aymen, 83–85
Sobottka Thomas, 101–109
Steinbuch Rolf, 16–18
Sweeney James, 273–282

Talbi El-Ghazali, 6–15, 155–157, 244–246, 283–290, 314–321
Taleb-Ahmed Abdelmalik, 2–5
Tamura Kenichi, 322–324
Tatsis Vasileios, 86–94
Terki Nadjiba, 31–41
Tetouani Samir, 42–49
Thivet Eric, 325–327
Tichy Tomas, 62
Torres Bispo Dos Santos Leonardo, 165–174
Torres Leonor, 121–123
Toumi Abida, 31–41
Touzout Fayçal A., 521–530

Ulrich Maximilian, 101–109

Varlet Eric, 283–290
Vitale Alessandro, 6–15
Vukašinović Vida, 426–434

Yalaoui Alice, 309–311, 325–327, 483–485
Yalaoui Farouk, 50–52, 325–327, 531–533, 561–563, 574–576
Yamina Mohamed Ben Ali, 399–406
Yassine Adnan, 450–473

Zemzami Maria, 474–476
Zouadi Tarik, 483–485

Sponsors