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**Matheuristics** 

Vittorio Maniezzo, Thomas Stützle and Stefan Voß

## **Matheuristics**

# Hybridizing Metaheuristics and Mathematical Programming

edited by

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## **Preface**

The field of metaheuristics has traditionally been very receptive to proposals about how to structure algorithms in order to effectively solve optimization problems. Innovation of solution approaches has always been one of the traits of the field, and design paradigms have succeeded as inspiration for algorithm designers: inspiration from nature, improvements of local search, logics and probability, etc. The paradigm put forth in this book represents a "back to the roots" for computational optimization: use mathematics!

Albeit people working on metaheuristics have always been full citizens of the mathematical programming and operations research community and the main results have always been well-known, interactions (cross-fertilizations as it used to be fashionable to say) have always been limited. Core mathematical programming (MP) approaches have little to share with metaheuristics and mainstream metaheuristics include little or no mathematics.

This book shows how both metaheuristics and MP can leverage on one another. It shows how it is possible both to include MP techniques into metaheuristic frameworks and metaheuristic concepts inside MP systems. This follows a trend in hybridization, which appeared in several forms in the last years: metaheuristics are being hybridized with artificial intelligence, with constraint programming, with statistics, not to mention among themselves. However, the combination of metaheuristics and MP has a set-apart condition. Including MP techniques for a metaheuristic designer does not mean looking for contributions, which could possibly derive from another research area, it means looking inside one's own cultural baggage, it means using in a different way something one has already had experience with.

The contributions included in this collection comprise invited chapters that give an overview on specific topics in matheuristics and articles that were selected among the presentations at the *Matheuristics 2008* workshop. This was the second edition of a workshop series centered on the above ideas, having the stated objective of giving group identity to all researchers who share the interest in the synergies existing between the two related research lines metaheuristics and MP. The success of the first edition, which was upon

vi Preface

invitation only, suggested to open to submissions for the second. We scored an higher than 30% rejection rate at the conference, and acceptance barriers were high also for the present volume. We thus believe to have collected a set of good quality contributions, which will help in increasing the awareness of the possibilities offered by this new research direction.

The book includes 11 contributions, which span over a variety of topics.

Caserta and Voß open with an up-to-date overview of the field of metaheuristics, which helps to frame the matheuristics contributions in the more general context of metaheuristics advances.

Fischetti, Lodi and Salvagnin provide a survey on the use of mixed integer programming (MIP) solvers as subroutines for solving NP-hard subproblems, which arise while solving a more complex problem. Different success cases are reported, which follow this general idea.

Puchinger, Raidl and Pirkwieser review possibilities of how to use greedy heuristics, iterative improvement algorithms, and metaheuristics to improve the performance of MIP solvers. The possibilities for doing so are varied, and range from providing good quality starting solutions to using metaheuristics for cut separation or column generation.

Dumitrescu and Stützle review approaches that combine local search and metaheuristics with MP techniques. In particular, they focus on algorithms where the metaheuristic is the master solver and MP techniques are used to solve subproblems arising in the search process.

Boschetti, Maniezzo and Roffilli show how it is possible to use decomposition techniques, which were originally conceived as tools for exact optimization, as metaheuristic frameworks. The general structure of each of the best known decomposition approaches (Lagrangean, Benders and Dantzig-Wolfe) can, in fact, be considered as a general structure for a corresponding metaheuristic.

Gutjahr proposes a more theoretical contribution. His chapter gives an overview on techniques for proving convergence of metaheuristics to optimal or sufficiently good solutions. Two particularly interesting topics that are covered are convergence of metaheuristic algorithms for stochastic combinatorial optimization, and estimation of expected runtime, i.e., of the time needed by a metaheuristic to hit the first time a solution of a required quality.

The remaining papers address specific problems by means of matheuristic algorithms, rather than presenting general overviews as the ones above.

Dolgui, Eremeev and Guschinskaya address the problem of balancing transfer lines with multi-spindle machines. They present two algorithms that integrate traditional metaheuristics and a MIP solver. Specifically, they design a GRASP and a genetic algorithm, which both use a MIP solver as a subroutine for solving subproblems arising in the search process of the metaheuristics.

Gruber and Raidl work on exact algorithms for the bounded diameter minimum spanning tree problem. They use simple heuristics and a tabu search algorithm for solving the separation problem in their branch-and-cut algo-

Preface vii

rithm. Moreover, they include in their approach a variable neighborhood descent for finding good primal solutions.

Liberti, Nannicini and Mladenović present a work in mixed integer non-linear programming, having the objective of identifying good quality, or at least feasible solutions for difficult instances. They propose a method, called RECIPE (for Relaxed-Exact Continuous-Integer Problem Exploration), combining variable neighborhood search, local branching, sequential quadratic programming and branch-and-bound.

Mitrović-Minić and Punnen present their method consisting in a local search where large neighborhoods are explored by means of ancillary MIP subproblems. They present results on the basic generalized assignment problem (GAP) and on the multi-resource GAP showing the potential of the approach.

Finally, Ulrich-Ngueveu, Prins, and Wolfler-Calvo study the m-peripatetic vehicle routing problem, which is a special vehicle routing problem, asking that each arc is used in the solution at most once for each set of m periods considered in the plan. The approach uses a perfect b-matching to define the candidate sets used in a granular tabu search algorithm.

We conclude expressing our gratitude to all authors who submitted their works to Matheuristics 2008 and to this post-conference collection, to the members of the international program committee and to all external reviewers. We are confident that this book, as a result of their joint effort, will provide a basis to support the increasing interest on the covered topics. We hope and believe that the result constitutes a significant achievement in the direction of establishing matheuristics as a credible tool for obtaining fast and reliable solutions to real-world problems.

Bologna, Brussels, Hamburg, April 2009 Vittorio Maniezzo Thomas Stützle Stefan Voß

# Contents

1	$\mathbf{Met}$	aheuris	tics: Intelligent Problem Solving	1	
	Marc	co Caser	ta and Stefan Voß		
	1.1	Introd	uction	1 5	
	1.2	1.2 Basic Concepts and Discussion			
		1.2.1	Local Search	-	
		1.2.2	Metaheuristics	7	
		1.2.3	Miscellaneous	14	
	1.3	A Tax	onomy	15	
	1.4	Hybrid	ls with Exact Methods	19	
	1.5	Genera	al Frames: A Pool-Template	22	
	1.6	Fine T	uning and Evaluation of Algorithms	24	
		1.6.1	Fine Tuning of Metaheuristics	24	
		1.6.2	Empirical Evaluation of Metaheuristics	26	
	1.7	Optim	ization Software Libraries	30	
	1.8	Conclu	sions	30	
	Refer	rences .		32	
<b>2</b>	Just	MIP i	t!	39	
	Matteo Fischetti, Andrea Lodi, and Domenico Salvagnin				
	2.1	Introd	$\operatorname{uction}$	40	
	2.2	MIPpi	ng Cut Separation	41	
		2.2.1	Pure Integer Cuts	43	
		2.2.2	Mixed Integer Cuts	44	
		2.2.3	A Computational Overview	47	
	2.3	MIPpi	ng Heuristics	50	
		2.3.1	Local Branching and Feasibility Pump	51	
		2.3.2	LB with Infeasible Reference Solutions	54	
		2.3.3	Computational Results	55	
	2.4	MIPpi	ng the Dominance Test	61	
		2.4.1	Borrowing Nogoods from Constraint Programming .	63	
		2.4.2	Improving the Auxiliary Problem	64	

x Contents

	Dofo	2.4.3	Computational Results	
3			ing: Enhancing Integer Programming	
			by Metaheuristics	
			nger, Günther R. Raidl, and Sandro Pirkwieser uction	
	3.1 Introduction			
	3.2		r Programming Techniques	
		3.2.1 $3.2.2$	Relaxations and Duality	
			LP-Based Branch-and-Bound	
		3.2.3 $3.2.4$	Cutting Plane Algorithm and Branch-and-Cut 76 Column Generation and Branch-and-Price 77	
	3.3	_	Column Generation and Branch-and-Price	
	ა.ა	3.3.1	Initial Solutions	
		3.3.1	B&B Acting as Local Search Based Metaheuristic 80	
		3.3.2	Solution Merging	
		3.3.4	Metaheuristics and Lagrangian Relaxation 83	
	3.4		porative Hybrids	
	3.5		euristics for Cut and Column Generation	
	0.0	3.5.1	Cut Separation	
		3.5.2	Column Generation	
	3.6		Study: A Lagrangian Decomposition/EA Hybrid 87	
	0.0	3.6.1	The Knapsack Constrained Maximum Spanning	
		3.0.1	Tree Problem	
		3.6.2	Lagrangian Decomposition of the KCMST Problem 88	
		3.6.3	Lagrangian Heuristic	
		3.6.4	Evolutionary Algorithm for the KCMST 89	
		3.6.5	LD/EA Hybrid	
		3.6.6	Experimental Results	
			Study: Metaheuristic Column Generation	
		3.7.1	The Periodic Vehicle Routing Problem with Time	
			Windows	
		3.7.2	Set Covering Formulation for the PVRPTW 94	
		3.7.3	Column Generation for Solving the LP Relaxation . 95	
		3.7.4	Exact and Metaheuristic Pricing Procedures 96	
		3.7.5	Experimental Results	
	3.8	Conclu	usions	
	Refe	rences .		
4	Usag	ge of E	xact Algorithms to Enhance Stochastic Local	
	Search Algorithms			
	Irina		escu and Thomas Stützle	
	4.1 Introduction			
	4.2		ring large neighborhoods	
		4.2.1	NSP Example: Cyclic and Path Exchange	
			Neighborhoods	

Contents xi

	4.2.2	NSP Example: Dynasearch	. 111
	4.2.3	PNSP Example: Hyperopt Neighborhoods	. 112
	4.2.4	Other Approaches	
	4.2.5	Discussion	. 114
4.3	Enhan	cing Metaheuristics	. 115
	4.3.1	Example: Perturbation in Iterated Local Search	. 115
	4.3.2	Other Approaches	
	4.3.3	Discussion	. 118
4.4	Using	Branch-and-Bound Techniques in Constructive	
		Heuristics	. 118
	4.4.1	Example: Approximate Nondeterministic Tree	
	4.4.0	Search (ANTS)	
	4.4.2	Other Approaches	
4.5	-	ting the Structure of Good Solutions	
	4.5.1	Example: Heuristic Concentration	
	4.5.2	Example: Tour Merging	
	4.5.3	Discussion	
4.6	_	ting Information from Relaxations in Metaheuristics	
	4.6.1	Example: Simplex and Tabu Search Hybrid	
	4.6.2	Discussion	. 127
4.7	Conclu	isions	. 128
Refe	rences .		. 129
Dec	omposit	tion Techniques as Metaheuristic Frameworks	135
		etti, Vittorio Maniezzo, and Matteo Roffilli	. 100
5.1		uction	. 135
5.2		position Methods	
٠.2			
		Lagrangean Relaxation	1.57
	5.2.1	Lagrangean Relaxation	
	5.2.1 $5.2.2$	Dantzig-Wolfe Decomposition	. 138
53	5.2.1 5.2.2 5.2.3	Dantzig-Wolfe Decomposition	. 138 . 139
5.3	5.2.1 5.2.2 5.2.3 Metah	Dantzig-Wolfe Decomposition  Benders Decomposition euristics Derived from Decompositions	. 138 . 139 . 141
5.3	5.2.1 5.2.2 5.2.3 Metah 5.3.1	Dantzig-Wolfe Decomposition  Benders Decomposition  euristics Derived from Decompositions  A Lagrangean Metaheuristic	. 138 . 139 . 141 . 142
5.3	5.2.1 5.2.2 5.2.3 Metah 5.3.1 5.3.2	Dantzig-Wolfe Decomposition Benders Decomposition euristics Derived from Decompositions A Lagrangean Metaheuristic A Dantzig-Wolfe Metaheuristic	<ul><li>. 138</li><li>. 139</li><li>. 141</li><li>. 142</li><li>. 142</li></ul>
	5.2.1 5.2.2 5.2.3 Metah 5.3.1 5.3.2 5.3.3	Dantzig-Wolfe Decomposition Benders Decomposition euristics Derived from Decompositions A Lagrangean Metaheuristic A Dantzig-Wolfe Metaheuristic A Benders Metaheuristic	<ul><li>. 138</li><li>. 139</li><li>. 141</li><li>. 142</li><li>. 143</li></ul>
5.3	5.2.1 5.2.2 5.2.3 Metah 5.3.1 5.3.2 5.3.3 Single	Dantzig-Wolfe Decomposition Benders Decomposition euristics Derived from Decompositions A Lagrangean Metaheuristic A Dantzig-Wolfe Metaheuristic A Benders Metaheuristic Source Capacitated Facility Location	<ul><li>. 138</li><li>. 139</li><li>. 141</li><li>. 142</li><li>. 143</li></ul>
	5.2.1 5.2.2 5.2.3 Metah 5.3.1 5.3.2 5.3.3	Dantzig-Wolfe Decomposition  Benders Decomposition  euristics Derived from Decompositions.  A Lagrangean Metaheuristic.  A Dantzig-Wolfe Metaheuristic  A Benders Metaheuristic.  Source Capacitated Facility Location  Solving the SCFLP with a Lagrangean	. 138 . 139 . 141 . 142 . 143 . 144
	5.2.1 5.2.2 5.2.3 Metah 5.3.1 5.3.2 5.3.3 Single 5.4.1	Dantzig-Wolfe Decomposition Benders Decomposition euristics Derived from Decompositions A Lagrangean Metaheuristic A Dantzig-Wolfe Metaheuristic A Benders Metaheuristic Source Capacitated Facility Location Solving the SCFLP with a Lagrangean Metaheuristic	. 138 . 139 . 141 . 142 . 143 . 144
	5.2.1 5.2.2 5.2.3 Metah 5.3.1 5.3.2 5.3.3 Single	Dantzig-Wolfe Decomposition Benders Decomposition euristics Derived from Decompositions A Lagrangean Metaheuristic A Dantzig-Wolfe Metaheuristic A Benders Metaheuristic Source Capacitated Facility Location Solving the SCFLP with a Lagrangean Metaheuristic Solving the SCFLP with a Dantzig-Wolfe	. 138 . 139 . 141 . 142 . 143 . 144
	5.2.1 5.2.2 5.2.3 Metah 5.3.1 5.3.2 5.3.3 Single 5.4.1 5.4.2	Dantzig-Wolfe Decomposition Benders Decomposition euristics Derived from Decompositions A Lagrangean Metaheuristic A Dantzig-Wolfe Metaheuristic A Benders Metaheuristic Source Capacitated Facility Location Solving the SCFLP with a Lagrangean Metaheuristic Solving the SCFLP with a Dantzig-Wolfe Metaheuristic	. 138 . 139 . 141 . 142 . 142 . 143 . 144 . 146
5.4	5.2.1 5.2.2 5.2.3 Metah 5.3.1 5.3.2 5.3.3 Single 5.4.1 5.4.2	Dantzig-Wolfe Decomposition Benders Decomposition euristics Derived from Decompositions A Lagrangean Metaheuristic A Dantzig-Wolfe Metaheuristic A Benders Metaheuristic Source Capacitated Facility Location Solving the SCFLP with a Lagrangean Metaheuristic Solving the SCFLP with a Dantzig-Wolfe Metaheuristic Solving the SCFLP with a Benders Metaheuristic Solving the SCFLP with a Benders Metaheuristic	. 138 . 139 . 141 . 142 . 143 . 144 . 146 . 147 . 149
	5.2.1 5.2.2 5.2.3 Metah 5.3.1 5.3.2 5.3.3 Single 5.4.1 5.4.2 5.4.3 Compt	Dantzig-Wolfe Decomposition Benders Decomposition euristics Derived from Decompositions A Lagrangean Metaheuristic A Dantzig-Wolfe Metaheuristic A Benders Metaheuristic Source Capacitated Facility Location Solving the SCFLP with a Lagrangean Metaheuristic Solving the SCFLP with a Dantzig-Wolfe Metaheuristic Solving the SCFLP with a Benders Metaheuristic utational Results	. 138 . 139 . 141 . 142 . 143 . 144 . 146 . 147 . 149 . 150
5.4	5.2.1 5.2.2 5.2.3 Metah 5.3.1 5.3.2 5.3.3 Single 5.4.1 5.4.2 5.4.3 Compu	Dantzig-Wolfe Decomposition Benders Decomposition euristics Derived from Decompositions. A Lagrangean Metaheuristic. A Dantzig-Wolfe Metaheuristic A Benders Metaheuristic Source Capacitated Facility Location Solving the SCFLP with a Lagrangean Metaheuristic. Solving the SCFLP with a Dantzig-Wolfe Metaheuristic. Solving the SCFLP with a Benders Metaheuristic. utational Results. Lagrangean Metaheuristic.	. 138 . 139 . 141 . 142 . 143 . 144 . 146 . 147 . 150 . 151
5.4	5.2.1 5.2.2 5.2.3 Metah 5.3.1 5.3.2 5.3.3 Single 5.4.1 5.4.2 5.4.3 Compt 5.5.1 5.5.2	Dantzig-Wolfe Decomposition Benders Decomposition euristics Derived from Decompositions. A Lagrangean Metaheuristic. A Dantzig-Wolfe Metaheuristic A Benders Metaheuristic Source Capacitated Facility Location Solving the SCFLP with a Lagrangean Metaheuristic. Solving the SCFLP with a Dantzig-Wolfe Metaheuristic. Solving the SCFLP with a Benders Metaheuristic. utational Results. Lagrangean Metaheuristic Dantzig-Wolfe Metaheuristic	. 138 . 139 . 141 . 142 . 143 . 144 . 146 . 147 . 149 . 150 . 151
5.4	5.2.1 5.2.2 5.2.3 Metah 5.3.1 5.3.2 5.3.3 Single 5.4.1 5.4.2 5.4.3 Compt 5.5.1 5.5.2 5.5.3	Dantzig-Wolfe Decomposition Benders Decomposition euristics Derived from Decompositions A Lagrangean Metaheuristic A Dantzig-Wolfe Metaheuristic A Benders Metaheuristic Source Capacitated Facility Location Solving the SCFLP with a Lagrangean Metaheuristic Solving the SCFLP with a Dantzig-Wolfe Metaheuristic Solving the SCFLP with a Benders Metaheuristic utational Results Lagrangean Metaheuristic Dantzig-Wolfe Metaheuristic Benders Metaheuristic	. 138 . 139 . 141 . 142 . 143 . 144 . 146 . 147 . 150 . 151 . 153
5.4 5.5	5.2.1 5.2.2 5.2.3 Metah 5.3.1 5.3.2 5.3.3 Single 5.4.1 5.4.2 5.4.3 Compt 5.5.1 5.5.2 5.5.3 Conclu	Dantzig-Wolfe Decomposition Benders Decomposition euristics Derived from Decompositions. A Lagrangean Metaheuristic. A Dantzig-Wolfe Metaheuristic A Benders Metaheuristic Source Capacitated Facility Location Solving the SCFLP with a Lagrangean Metaheuristic. Solving the SCFLP with a Dantzig-Wolfe Metaheuristic. Solving the SCFLP with a Benders Metaheuristic. utational Results. Lagrangean Metaheuristic Dantzig-Wolfe Metaheuristic	. 138 . 139 . 141 . 142 . 143 . 144 . 146 . 147 . 149 . 150 . 151 . 153 . 153

xii Contents

6		vergence Analysis	
	of M	Ietaheuristics	159
	Walt	er J. Gutjahr	
	6.1	Introduction	159
	6.2	A Generic Metaheuristic Algorithm	161
	6.3	Convergence	164
		6.3.1 Convergence Notions	164
		6.3.2 Best-So-Far Convergence	165
		6.3.3 Model Convergence	167
	6.4	Proving Convergence	169
		6.4.1 Proving Best-So-Far Convergence	169
		6.4.2 Proving Model Convergence	169
	6.5	Convergence for Problems with Noise	175
	6.6	Convergence Speed	178
	6.7	Conclusions	183
	Refer	rences	184
_			
7		P-based GRASP and Genetic Algorithm for Balancing	400
		nsfer Lines	189
		andre Dolgui, Anton Eremeev, and Olga Guschinskaya	400
	7.1	Introduction	
	7.2	Problem Statement	
	7.3	Greedy Randomized Adaptive Search Procedure	
		7.3.1 Construction Phase	
	<del></del> 4	7.3.2 Improvement Phase	
	7.4	Genetic Algorithm	
	7.5	Experimental Results	
		7.5.1 Problem Instances	
		7.5.2 Experimental Settings	
		7.5.3 Results	
	7.6	Conclusions	
	Refe	rences	207
8	(Me	ta-)Heuristic Separation of Jump Cuts in a	
•	•	nch&Cut Approach for the Bounded Diameter	
		imum Spanning Tree Problem	209
		in Gruber and Günther R. Raidl	
	8.1	Introduction	209
	8.2	Previous Work	
	8.3	The Jump Model	
	8.4	Jump Cut Separation	
	0	8.4.1 Exact Separation Model	
		8.4.2 Simple Construction Heuristic $C^A$	
		8.4.3 Constraint Graph Based Construction Heuristic $C^B$	
		8.4.4 Local Search and Tabu Search	
	8.5	Primal Heuristics	
	8.6	Computational Results	

Contents xiii

	8.7	Conclusions and Future Work		
	Refer	rences	. 228	
9	A Good Recipe for Solving MINLPs			
	Leo I	Liberti, Giacomo Nannicini, and Nenad Mladenović		
	9.1	Introduction		
	9.2	The Basic Ingredients		
		9.2.1 Variable Neighbourhood Search	. 233	
		9.2.2 Local Branching	. 234	
		9.2.3 Branch-and-Bound for cMINLPs	. 234	
		9.2.4 Sequential Quadratic Programming	. 235	
	9.3	The RECIPE Algorithm	. 236	
		9.3.1 Hyperrectangular Neighbourhood Structure	. 236	
	9.4	Computational Results	. 238	
		9.4.1 MINLPLib	. 239	
	9.5	Conclusion	. 242	
	Refer	rences	. 243	
10	Voni	able Intensity Local Search	245	
10		ana Mitrović-Minić and Abraham P. Punnen	. 240	
	10.1	Introduction	245	
	10.1	The General VILS Framework		
	10.2	Experimental Studies		
	10.3 $10.4$	Conclusion		
	-	cences		
11		ybrid Tabu Search for the <i>m</i> -Peripatetic Vehicle	250	
		ting Problem	. 253	
		ra Ulrich Ngueveu, Christian Prins, and Roberto Wolfler		
	Calvo			
	11.1	Introduction		
	11.2	Tabu Search	. 255	
		11.2.1 Initial Solution Heuristic and Neighborhood	~	
		Structure		
		11.2.2 Penalization and Tabu List Management		
	11.3	Hybridization with $b$ -Matching and Diversification		
		11.3.1 <i>b</i> -Matching		
		11.3.2 Hybridization		
		11.3.3 Diversification Procedure		
	11.4	Computational Analysis		
		11.4.1 VRP and <i>m</i> -PSP		
		11.4.2 $m$ -PVRP with $2 \le m \le 7$		
	11.5	Conclusion		
	Refer	rences	. 264	
Ind	lov		. 267	
THO	ICX		. 407	

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