

Badania naukowe dotyczące budowy systemów wspomagania decyzji opartych na sztucznej inteligencji

Zbigniew Michalewicz Chief Scientist



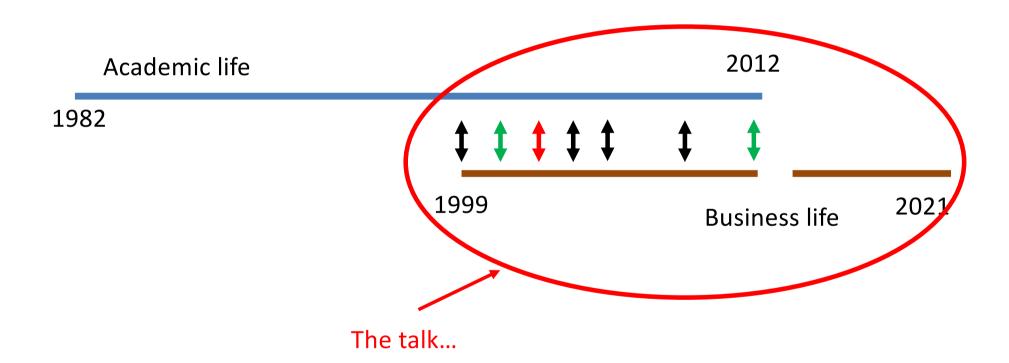


Outline of the talk

- > 1999: NuTech Solutions
- ➤ 2005: SolveIT Software
- ➤ 2014: Complexica
- ➤ Some thoughts on business applications and the EC research



Introduction





Business life

1999 - 2005







2005 - 2012







2014 -



Clients across a broad set of industries





























































Outline of the talk

- > 1999: NuTech Solutions
- ➤ 2005: SolveIT Software
- ➤ 2014: Complexica
- ➤ Some thoughts on business applications and the EC research

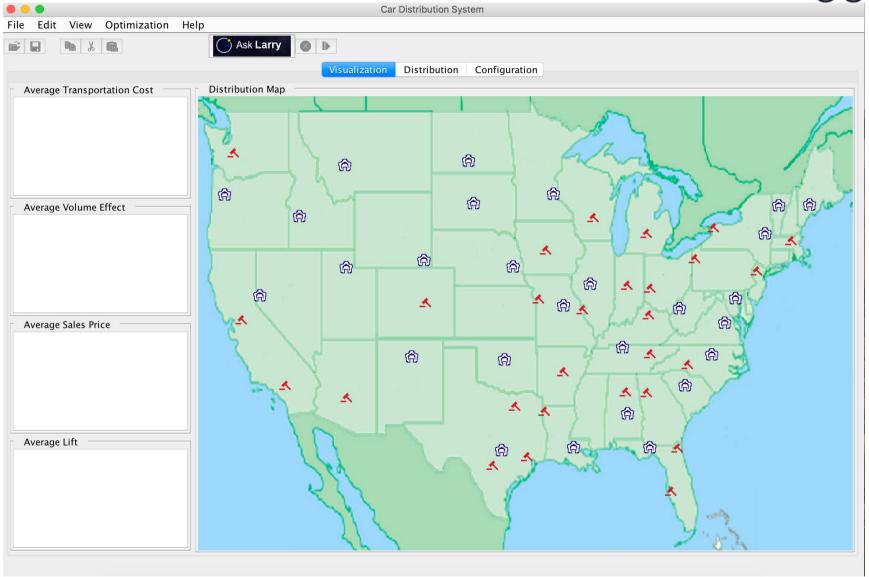


1999

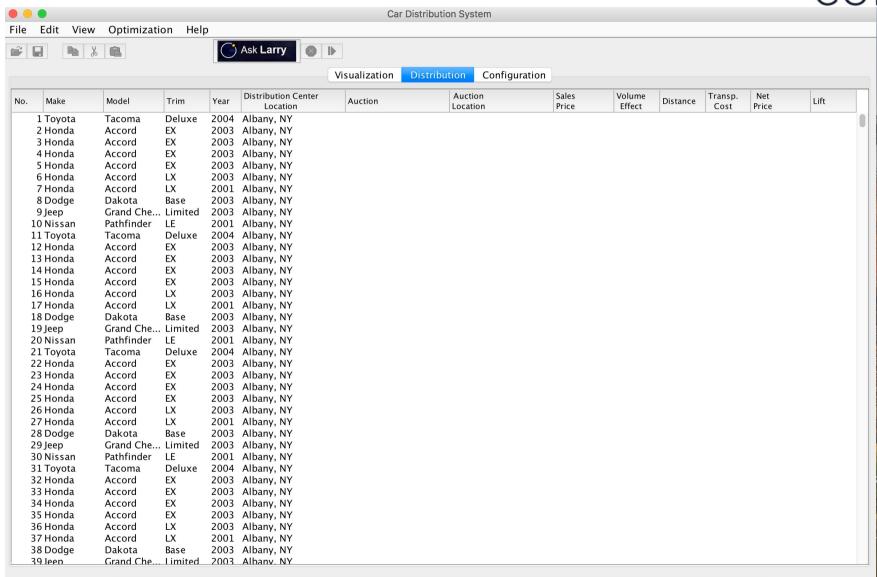


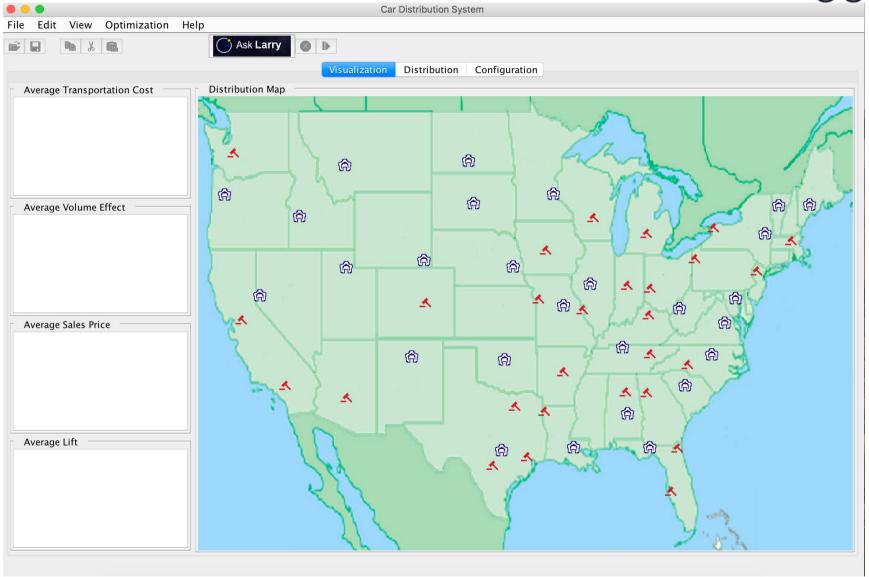
Car Distribution System (2001)

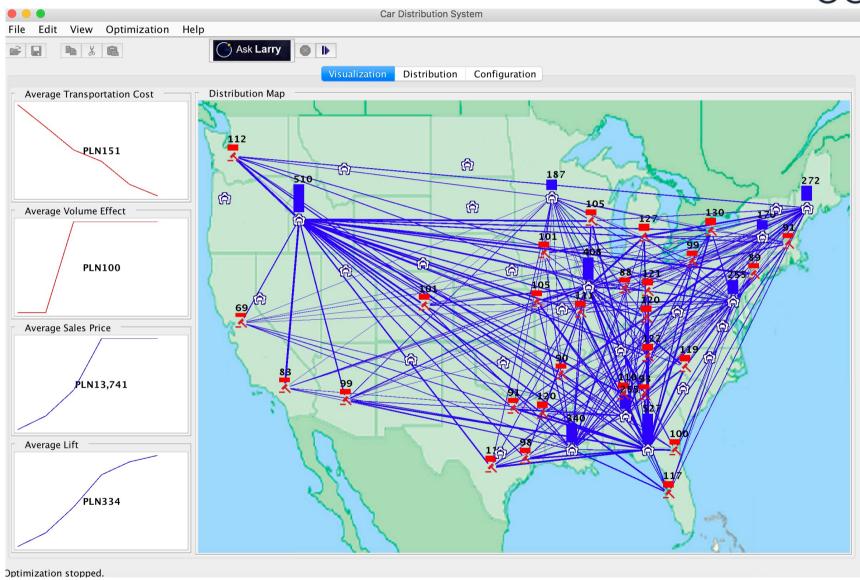
- GMAC (car financial organization) sells 1.2 million off-lease cars each year on various auction sites.
- Every single day, their remarketing team (23 analysts) uses business intelligence tools and reports to decide where to ship 4,000 7,000 off lease cars.
- The problem is impacted by demand, depreciation, transportation schedules, cost of capital, risk, changes in market conditions, recent decisions, and the volume effect.







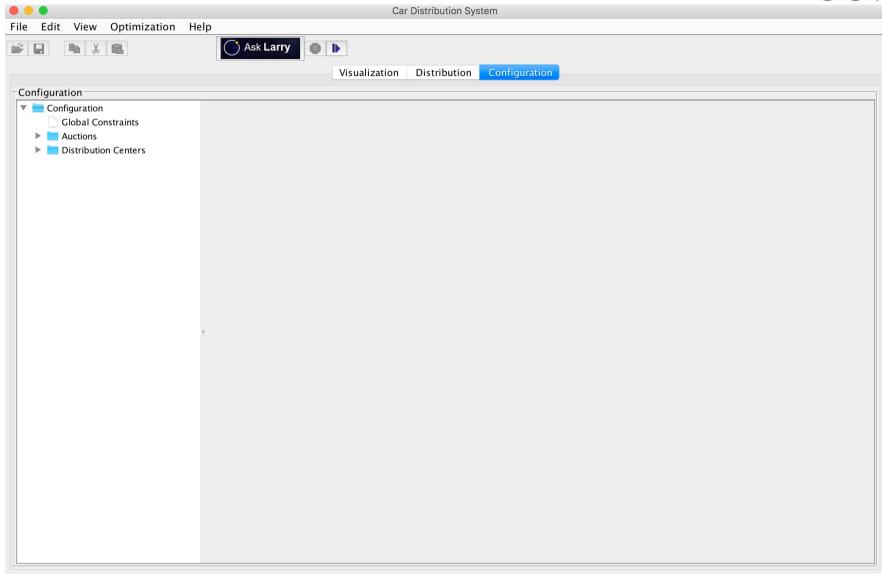




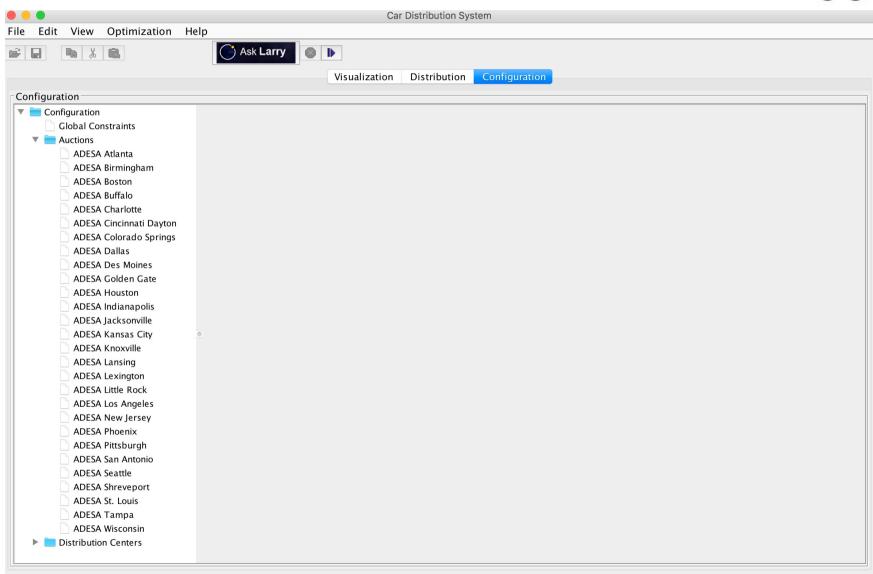


							Car Distributi	ion System						
e	Edit View	Optimizati	on Help)										
y III	- D- U	-			Ack Lovey	Th.								
	3 4 %			\cup	Ask Larry	I ▶								
						Visualiza	ation Distribu	ution Configuration						
						VISUAIIZ	ation Distribu	Configuration						
No.	Make	Model	Trim	Year	Distribution Center	Auctio	n	Auction	Sales	Volume	Distance	Transp.	Net	Lift
NO.	Make	Model	111111	Teal	Location	Auctio	"	Location	Price	Effect		Cost	Price	LIIL
	1 Toyota	Tacoma	Deluxe		Albany, NY		A Shreveport	Shreveport, LA	PLN 10,403		1299		,	
	2 Honda	Accord	EX		Albany, NY		A Knoxville	Lenoir City, TN	PLN 14,853	PLN73	732		,	
	3 Honda	Accord	EX		Albany, NY	ADES	A New Jersey	Manville, NJ	PLN 15,057	PLN68	151	PLN59	PLN14,998	
	4 Honda	Accord	EX	2003	Albany, NY	ADES	A Cincinnati D	Franklin, OH	PLN15,270	PLN81	588	PLN148	PLN15,122	
	5 Honda	Accord	EX	2003	Albany, NY	ADES	A Cincinnati D	. Franklin, OH	PLN 14,790	PLN79	588	PLN148	PLN14,642	PLN27
	6 Honda	Accord	LX	2003	Albany, NY	ADES	A Boston	Framingham, MA	PLN13,317	PLN97	121	PLN37	PLN13,280	PLN25
	7 Honda	Accord	LX	2001	Albany, NY	ADES	A Pittsburgh	Mercer, PA	PLN9,965	PLN57	346	PLN113	PLN9,852	PLN6
	8 Dodge	Dakota	Base	2003	Albany, NY	ADES/	A Phoenix	Chandler, AZ	PLN13,560	PLN72	2152	PLN493	PLN13,067	-PLN24
	9 Jeep	Grand Che	Limited	2003	Albany, NY	ADES/	A Little Rock	North Little Rock, AR	PLN 17,787	PLN95	1128	PLN258	PLN17,529	PLN23
1	0 Nissan	Pathfinder	LE	2001	Albany, NY	ADES	A Little Rock	North Little Rock, AR	PLN 16,598	PLN88	1128	PLN258	PLN16,340	PLN19
1	1 Toyota	Tacoma	Deluxe	2004	Albany, NY	ADES	A Lexington	Lexington, KY	PLN 10,378	PLN55	645	PLN173	PLN10,205	PLN16
1	2 Honda	Accord	EX		Albany, NY	ADES	A Golden Gate	Tracy, CA	PLN 14,682	PLN72	2504	PLN485	PLN14,197	-PLN37
1	3 Honda	Accord	EX		Albany, NY	ADES	A Knoxville	Lenoir City, TN	PLN15,222	PLN75	732	PLN184		
	4 Honda	Accord	EX		Albany, NY		A Phoenix	Chandler, AZ	PLN15,153	PLN81	2152		,	
	5 Honda	Accord	EX		Albany, NY		A Lansing	Dimondale, MI	PLN14,775	PLN99	552		,	
	6 Honda	Accord	LX		Albany, NY		A Lansing	Dimondale, MI	PLN13,406	PLN90	552		PLN13,315	
	7 Honda	Accord	LX		Albany, NY		A Knoxville	Lenoir City, TN	PLN9,994	PLN49	732			
	8 Dodge	Dakota	Base		Albany, NY		A Boston	Framingham, MA	PLN13,606	PLN99	121	PLN37		
	9 Jeep		Limited		Albany, NY		A Los Angeles	Mira Loma, CA	PLN17,716	PLN80	2414		,	
	0 Nissan	Pathfinder	LE		Albany, NY		A St. Louis	Barnhart, MO	PLN16,483	PLN88	921		,	
	1 Toyota	Tacoma	Deluxe		Albany, NY		A St. Louis	Barnhart, MO	PLN 10,456		921			
	2 Honda	Accord	EX		Albany, NY		A Boston	Framingham, MA	PLN14,888		121	PLN37	,	
	3 Honda	Accord	EX		Albany, NY		A Phoenix	Chandler, AZ	PLN15,260		2152		,	
	4 Honda	Accord	EX		Albany, NY		A Boston	Framingham, MA	PLN15,260 PLN15,153		121		,	
			EX		Albany, NY			J ,	PLN13,133	PLN110	121	PLN37		
	5 Honda 6 Honda	Accord			• •		A Boston	Framingham, MA	PLN 14,677 PLN 13,255		1023		,	
_		Accord	LX		Albany, NY		A Des Moines	Grimes, IA		PLN65			- , -	
	7 Honda	Accord	LX		Albany, NY		A Jacksonville	Jacksonville, FL	PLN9,845	PLN48	953		PLN9,644	
	8 Dodge	Dakota	Base		Albany, NY		A New Jersey	Manville, NJ	PLN13,746	PLN62	151	PLN59	,	
	9 Jeep	Grand Che	Limited		Albany, NY		A Buffalo	Akron, NY	PLN17,711	PLN107	241	PLN52	,	
	0 Nissan	Pathfinder	LE		Albany, NY		A Charlotte	Charlotte, NC	PLN16,587	PLN82	642		,	
	1 Toyota	Tacoma	Deluxe		Albany, NY		A Boston	Framingham, MA	PLN10,269		121	PLN37	,	
	2 Honda	Accord	EX		Albany, NY		A Lansing	Dimondale, MI	PLN14,987		552		,	
	3 Honda	Accord	EX		Albany, NY		A Lexington	Lexington, KY	PLN 14,984	PLN80	645		, -	
	4 Honda	Accord	EX		Albany, NY		A Lansing	Dimondale, MI	PLN15,254		552	PLN91	,	
	5 Honda	Accord	EX		Albany, NY		A Little Rock	North Little Rock, AR	PLN 14,604	PLN78	1128		,	
	6 Honda	Accord	LX		Albany, NY		A Buffalo	Akron, NY	PLN 13,426		241	PLN52	,	
3	7 Honda	Accord	LX	2001	Albany, NY	ADES	A Boston	Framingham, MA	PLN10,018	PLN73	121	PLN37	PLN9,981	PLN18
3	8 Dodge	Dakota	Base	2003	Albany, NY	ADES/	A Tampa	Tampa, FL	PLN13,419	PLN60	1123	PLN229	PLN13,190	-PLN12
3	9 leen	Grand Che	Limited	2003	Albany, NY	ADES	A Indianapolis	Plainfield. IN	PI N17.856	PI N 72	686	PI N167	PI N17.689	PLN39

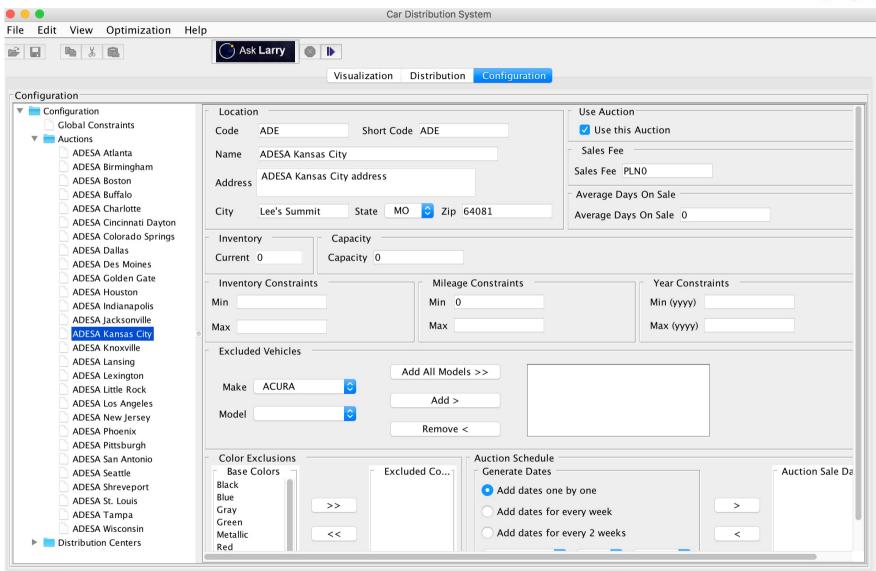




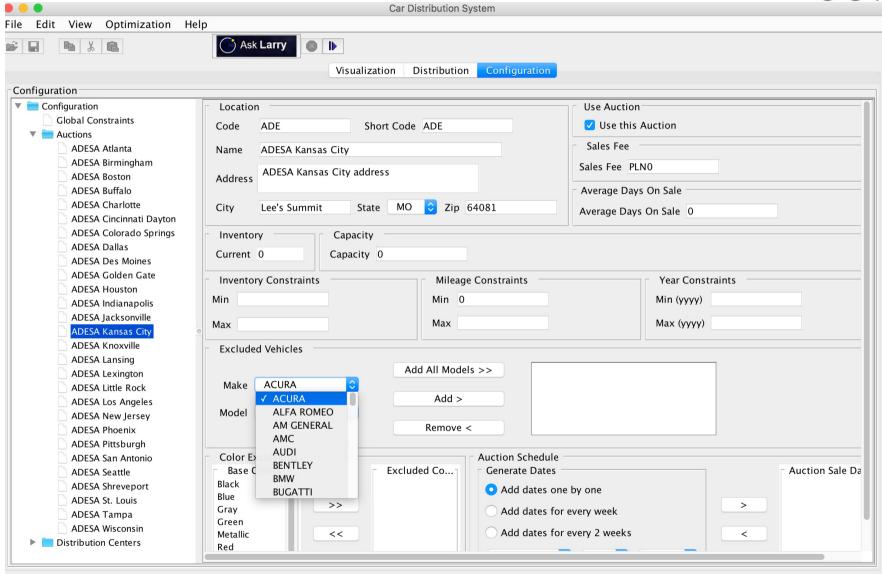




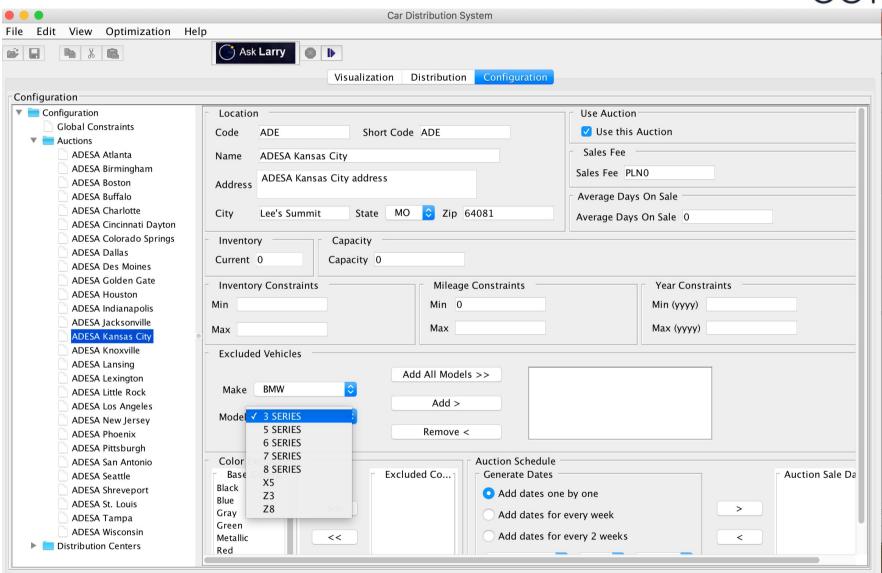




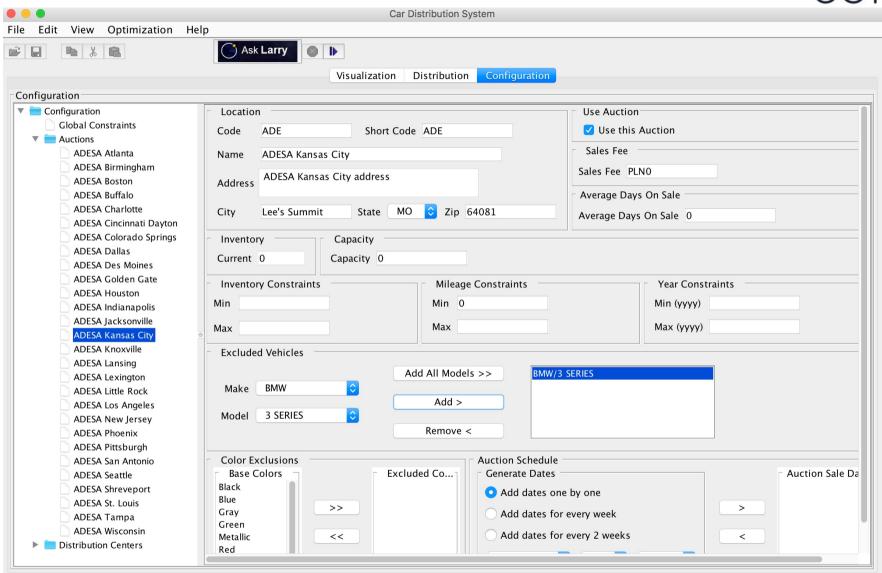














Results

Better: Net lift of \$213/car

Cheaper: 23 people down to 2

Faster: Minutes not man-days

Data-driven decisions that are consistent Predicted vs. actual comparisons; closed loop for making improvement



Results

Better: Net lift of \$213/car

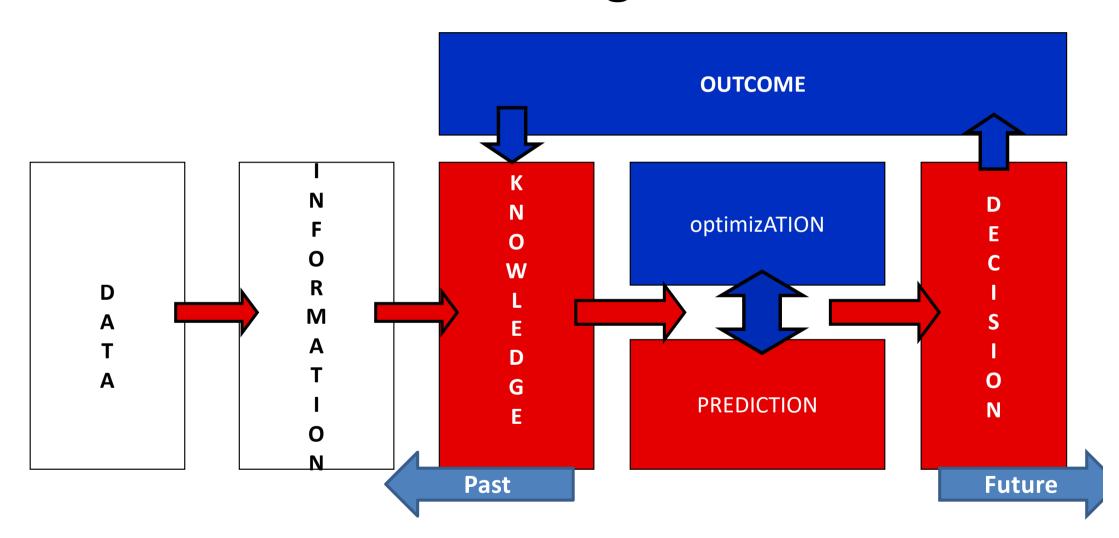
Cheaper: 23 people down to 2

Faster: Minutes not man-days

Data-driven decisions that are consistent Predicted vs. actual comparisons; closed loop for making improvement

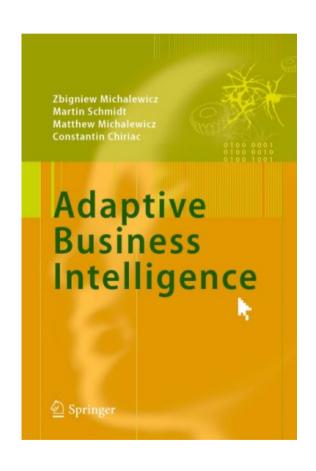


Adaptive Business Intelligence





Adaptive Business Intelligence



...how to combine prediction, optimization, and how to close the loop to create truly *intelligent* decision-support systems...



Outline of the talk

- > 1999: NuTech Solutions
- ➤ 2005: SolveIT Software
- ➤ 2014: Complexica
- ➤ Some thoughts on business applications and the EC research



2005



Consider decision support system for delivery of water tanks to farmers in Australia. Delivery decisions (many customers/orders & dealers, due dates, etc.) include:

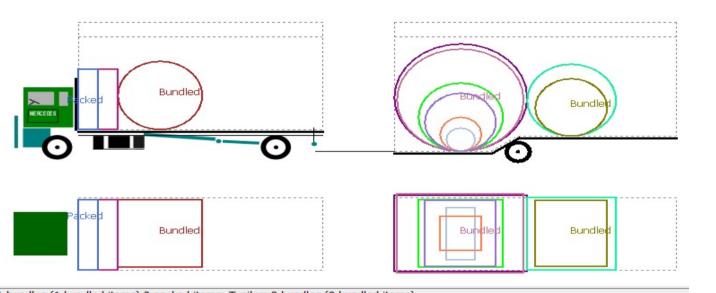
- ✓ selection of trucks / trailers
- ✓ selection of drivers
- ✓ packing (including bundling)
- ✓ routing (including dealers and unbundling sites)
- ✓ etc.



Each of these problems is hard to solve on its own.

For example, the problem of packing of goods on trucks and trailers cannot be solved with standard 2D or 3D packing algorithms, as different types of tanks can be packed in different ways, e.g. bundled inside each other, on top of each other, taking into account various constraints, in a pyramid stacking configuration, or as loose items.





lo. Transport	Tank	Pyramid	Order No.	Product	Product Group	Product	Height (m)	Width (m)	Depth (m)	Weight (kg)	Unbu
1 Truck	Packed		449746	TP40104	EVEREST K2	RECTAN	2.077	2.425	0.555	90	ONE STOP WATER SHOP
2 Truck	Packed		449746	TP33977	EVEREST K2	RECTAN	2.077	2.425	0.555	90	ONE STOP WATER SHOP
3 Truck	Bundle		449752	TP2843	8000L TANK	ROUND	2.325	2.341	2.341	151.75	ONE STOP WATER SHOP
4 Trailer	Bundle		449639	TP3413	22500L SQUA	ROUND	2.631	3.7	3.7	378.05	ONE STOP WATER SHO
5 Trailer	Bundle		449639	TP3369	22500L TANK	ROUND	2.72	3.53	3.53	378.25	ONE STOP WATER SHO
6 Trailer	Bundle		449639	TP2751	8000L TANK	ROUND	2.325	2.341	2.341	151.75	ONE STOP WATER SHO
7 Trailer	Bundle		449752	TP2621	5400L TANK	ROUND	2.268	1.986	1.986	113.75	ONE STOP WATER SHO
8 Trailer	Bundle		449752	TP19339	900L TANK	ROUND	1.17	1.16	1.16	30	ONE STOP WATER SHO
9 Trailer	Bundle		449746	TP19384	MINI-LINE 4	ROUND	1.788	0.788	0.788	26	ONE STOP WATER SHO
10 Trailer	Bundle		449752	TP2973	9000L TANK	ROUND	2.502	2.475	2.475	176.75	ONE STOP WATER SHO
11 Trailer	Bundle		448923	TP2690	5400L TANK	ROUND	2.268	1.986	1.986	113.75	ONE STOP WATER SHO



Further, many of these problems are connected in the sense that decisions made in one problem may impact some decisions for another problem:

- ✓ The packing and routing problems are intertwined, as the destination locations of items packed on a truck/trailer for a trip determine the final delivery destinations to be visited.
- ✓ Bundled water tanks can be unbundled only at specific agent locations, which has to be done prior to final delivery to customer locations.
- ✓ A decision of using a particular truck with a trailer for a trip may prevent another delivery which requires a driver with appropriate qualifications.



Global vs. silo optimisation

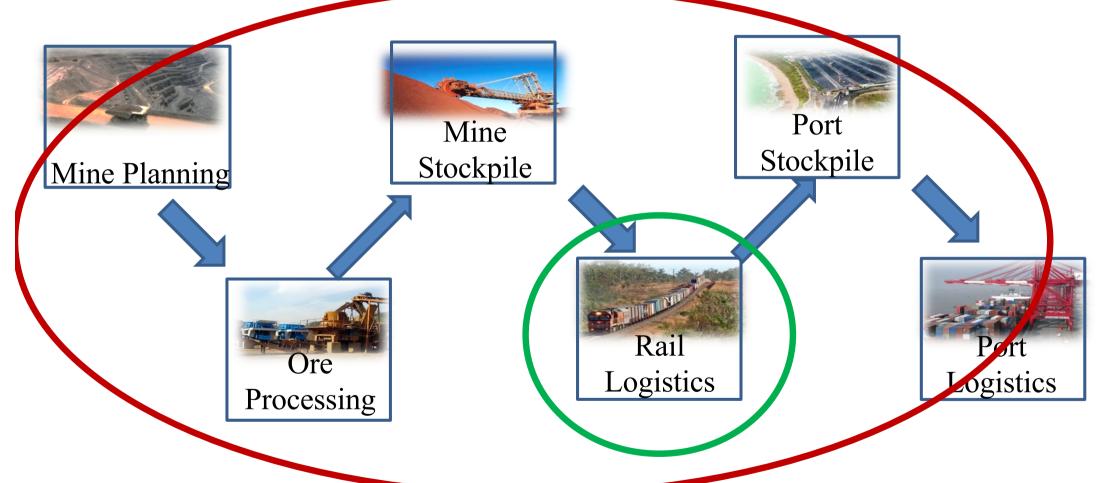
The optimal decision in one problem may prevent finding the overall optimal solution...

A thought from the past:

"Problems require holistic treatment. They cannot be treated effectively by decomposing them analytically into separate problems to which optimal solutions are sought."

R. Ackoff, *The Future of OR is Past*, JORS, 1979.

From Mine to Port Operations (2010) OMPLEXICA

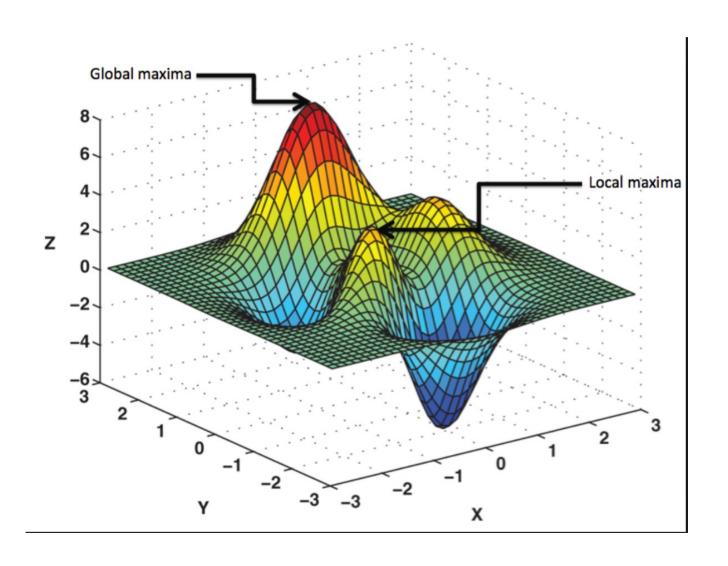


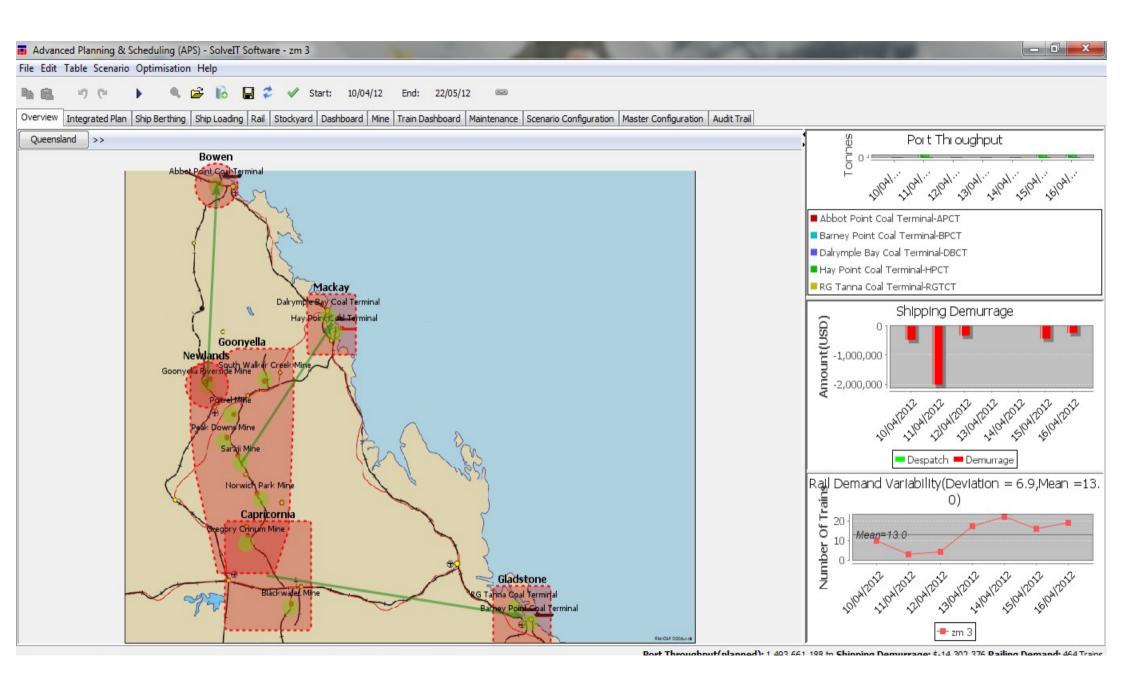
Local optimization

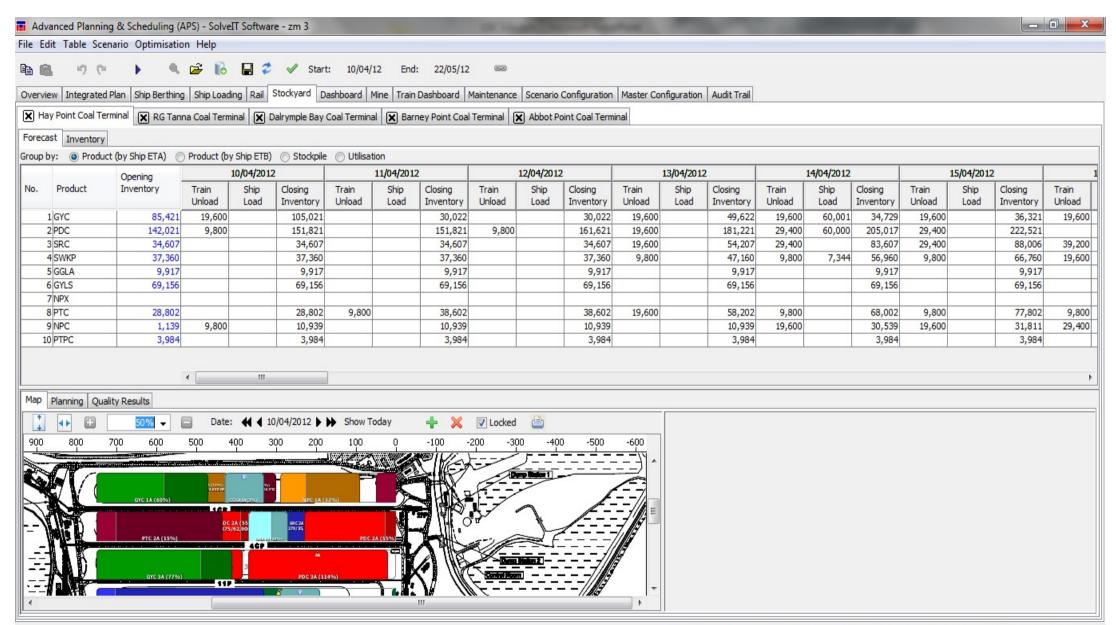
Global optimization

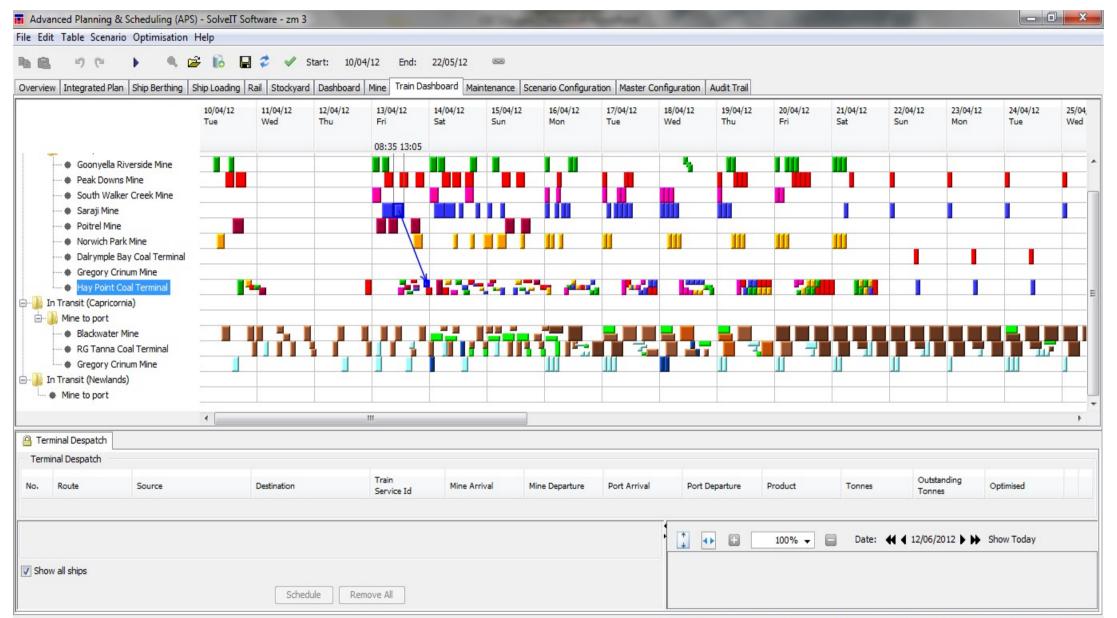


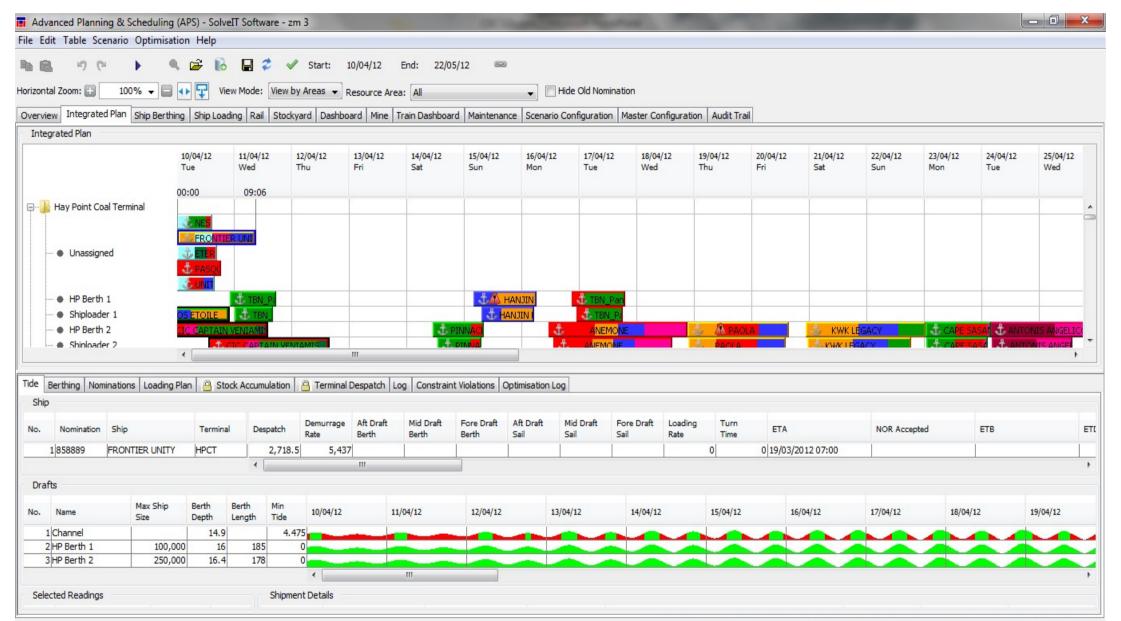
Global vs. Local optimization

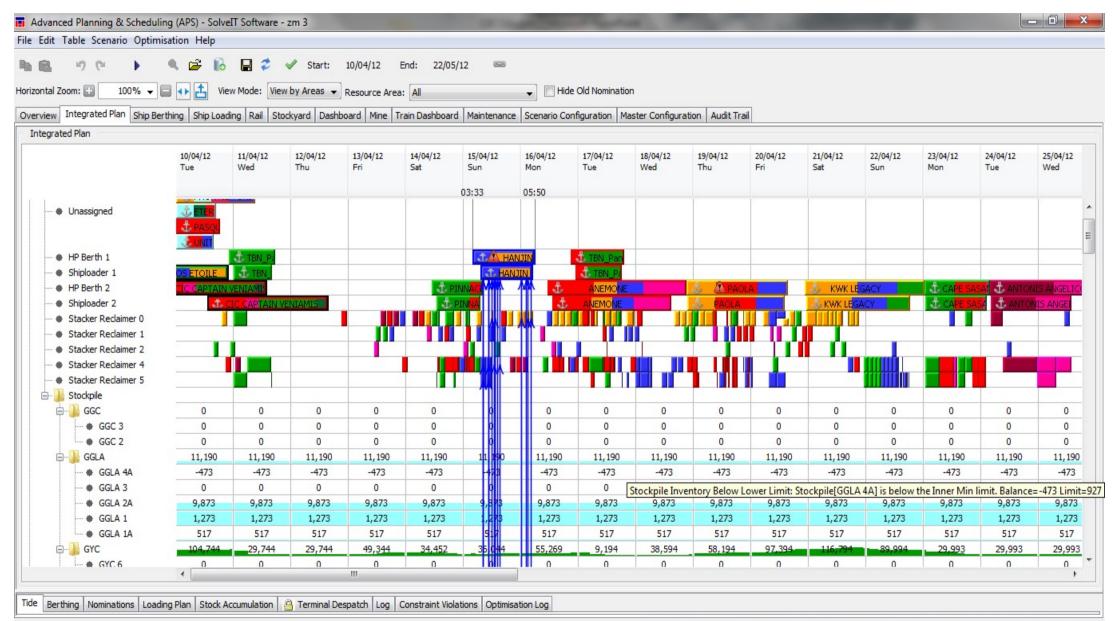


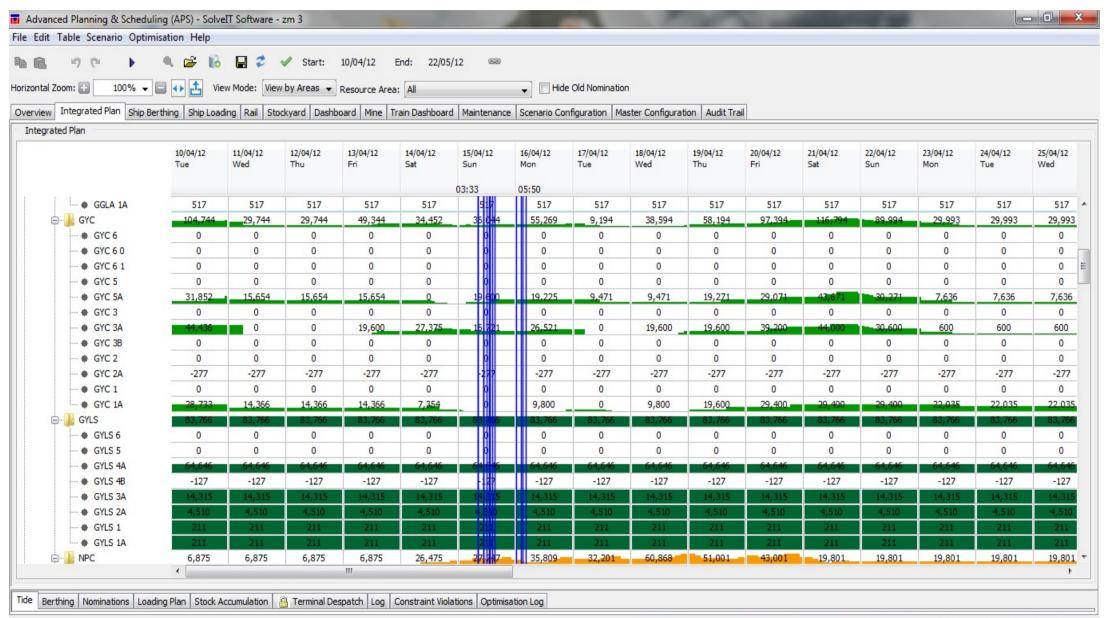


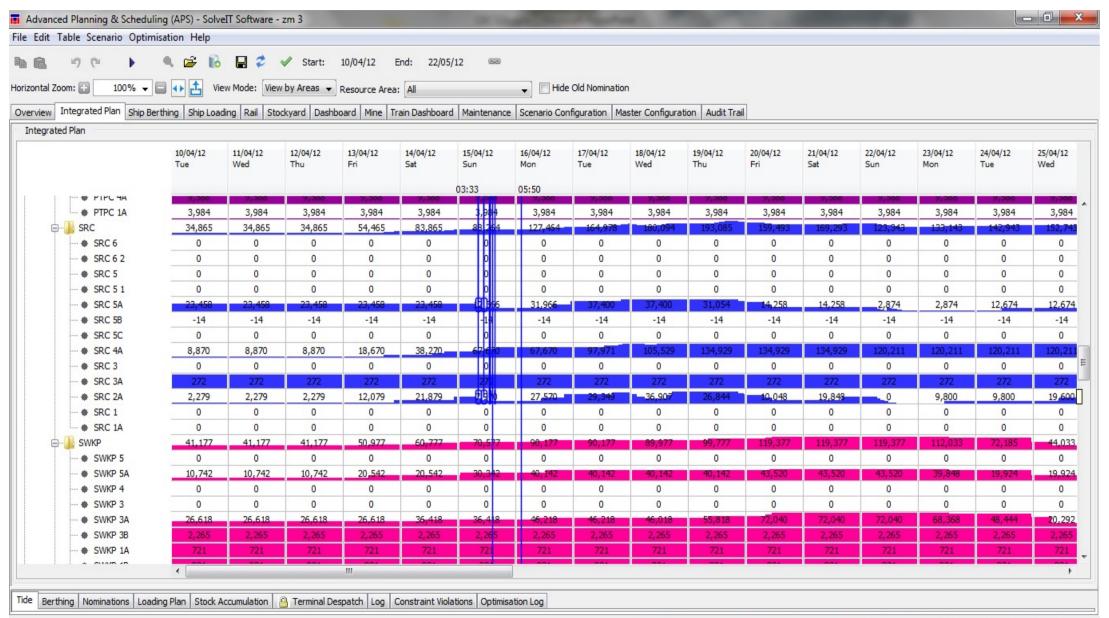


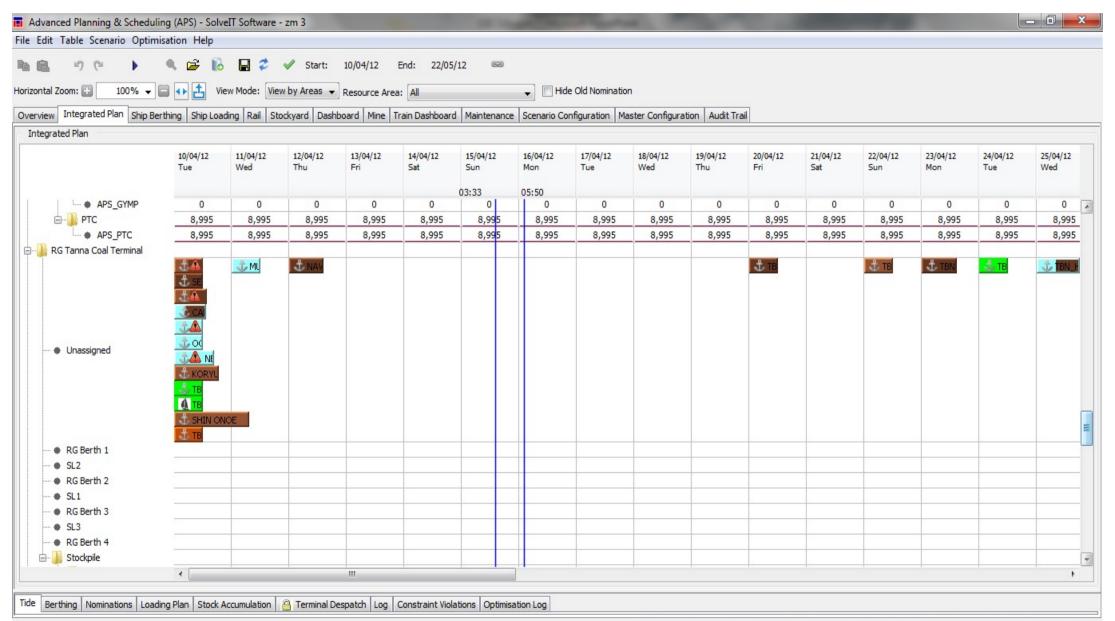


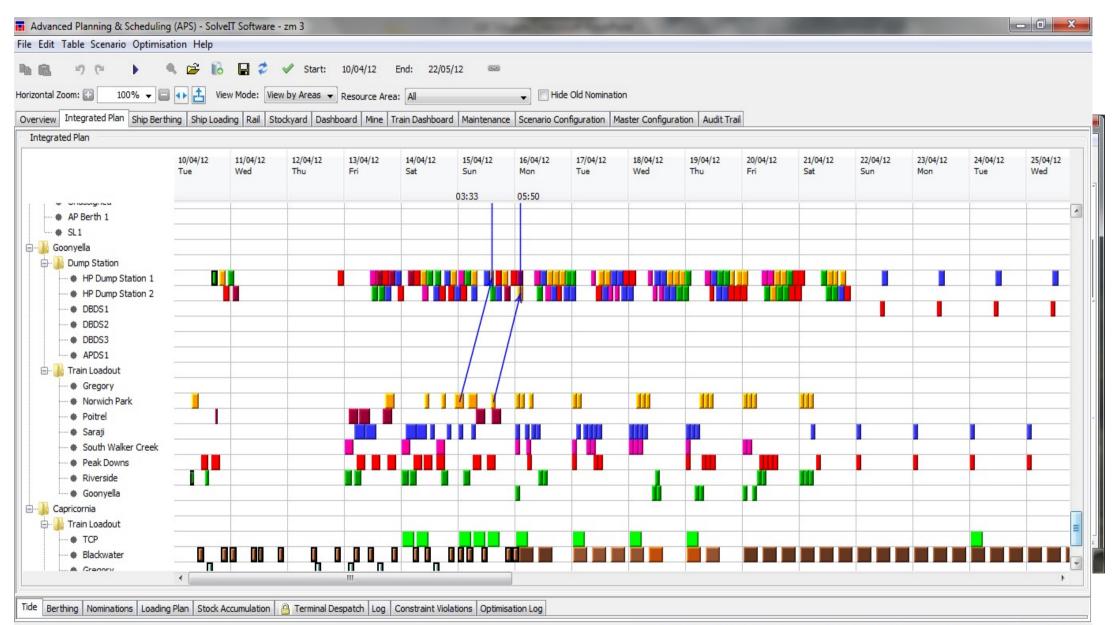




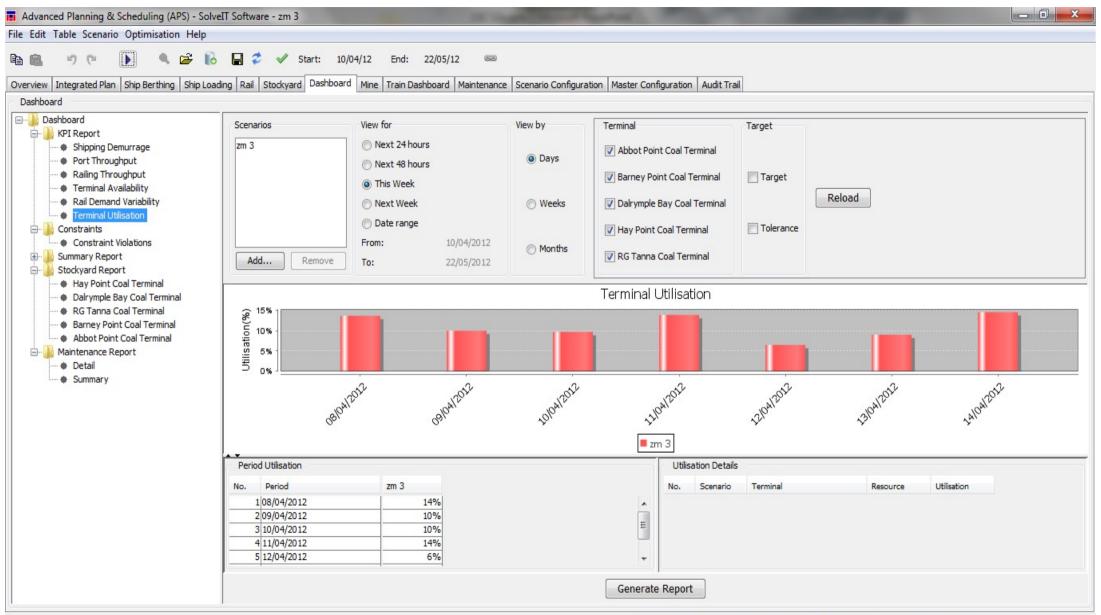




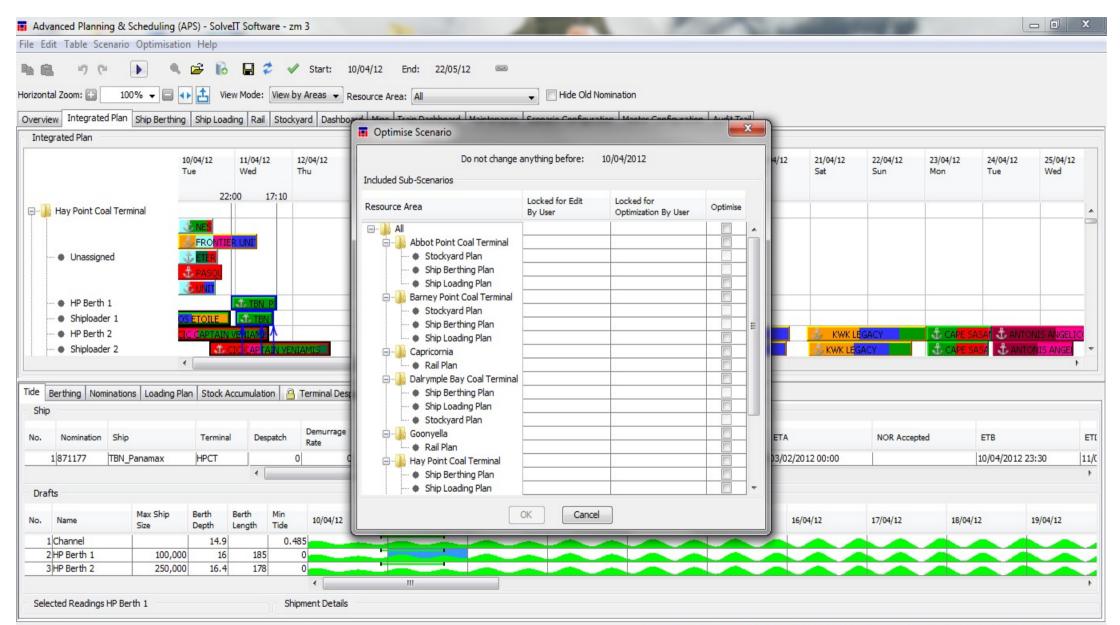




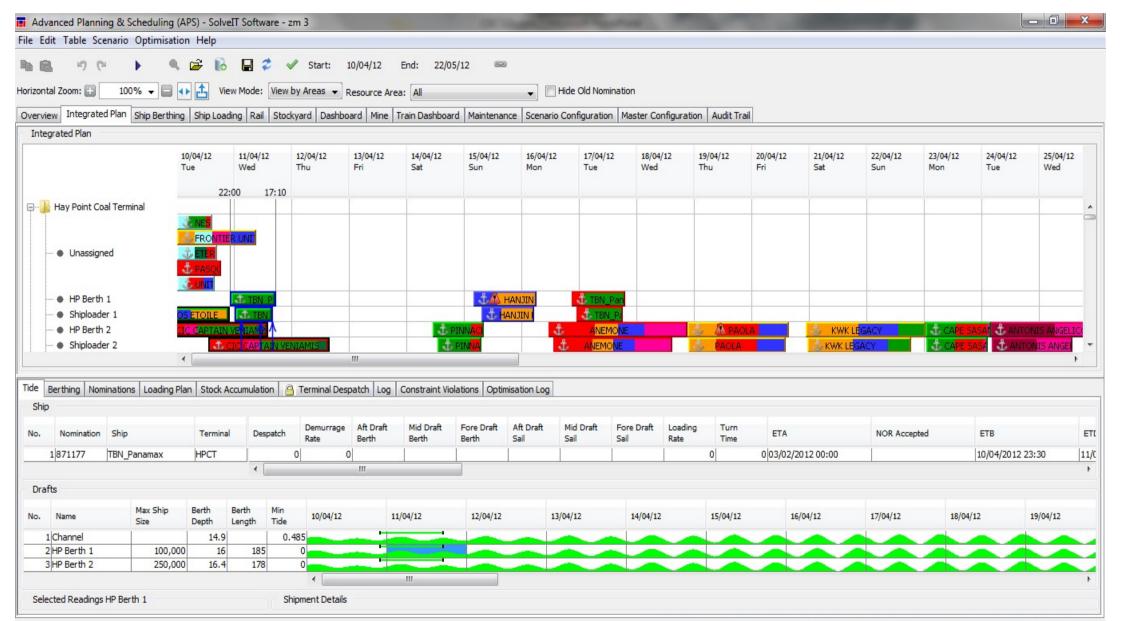
Part Throughout Inlanned 1: 1 403 661 188 to Chinning Demurrage: \$.14 302 376 Dailing Demand: 464 Trains

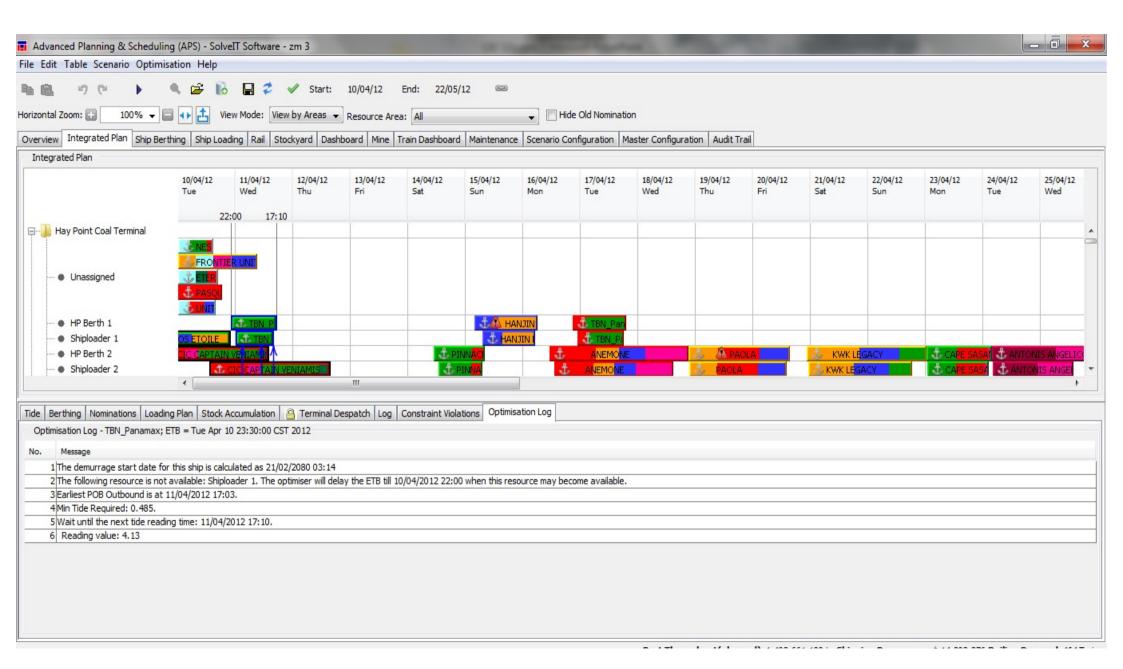


Part Throughout/ planned): 1 403 661 188 to Shipping Demurrage: 5-14 307 376 Dailing Demand: 464 Trains



Part Throughout/ planned): 1 403 661 188 to Chipping Demurrance \$.14 302 376 Dailing Demand: 464 Trains





Global optimization – consequences

- SolveIT Software was the first company to offer "global solutions" for supply chain problems (including what-ifs, optimization)
- SolveIT Software won every mining tender: Billiton Mitsubishi Alliance, Rio Tinto, Xstrata, Fortescue, BHP Iron Ore, Hancock, PNC, QR, etc.
- SolveIT Software was acquired by Schneider Electric in August 2012



Outline of the talk

- > 1999: NuTech Solutions
- ➤ 2005: SolveIT Software
- ➤ 2014: Complexica
- ➤ Some thoughts on business applications and the EC research





Promotional planning (2018)

We've all experienced product promotions, e.g.:

Sale! 50% off!

Buy one, get one free!

which manufacturers and retailers use to

- ✓ drive foot traffic into stores
- ✓ increase volume and market share
- ✓ build awareness for new products

These promotional activities are typically funded by both the retailer and participating manufacturer and can account for almost 20% of the revenue of fast-moving consumer goods (FMCG) companies.



Retailer: Mary's Market

State: NSW

Category: Snacks

A retailer with 500 stores across the country

	WK 1	WK 2	WK 3	WK 4	WK 5	WK 6	•••	WK 51	WK 52
Product 1	Υ	Υ		Υ	Υ				
Product 2	Υ		Υ		Υ	Υ			Υ
Product 3	Υ		Υ		Υ	Υ			Υ
Product 4			Υ						
Product 5	Υ			Υ					
Product 6	Υ	Υ		Υ					
•••									
Product 100	Υ			Υ	Υ			Υ	Υ

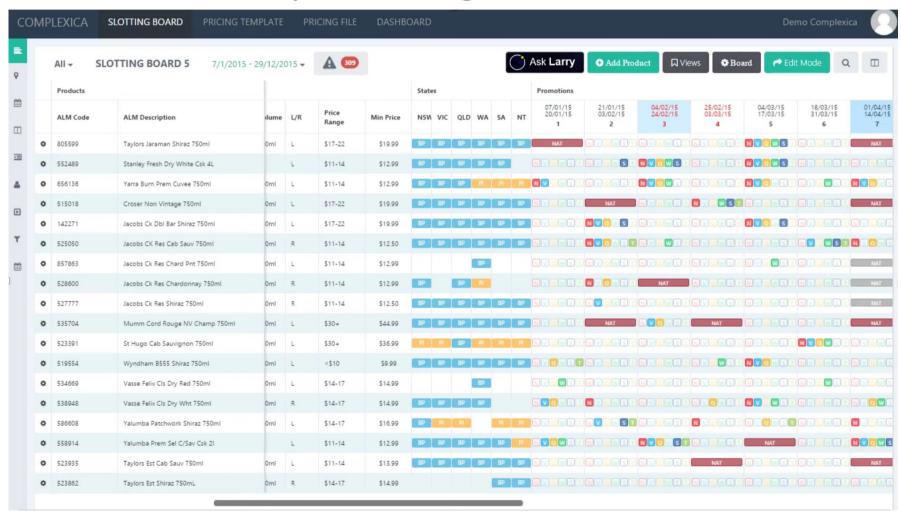


Retailer:	Mary's Market
State:	NSW
Category:	Snacks

	WK 1	WK 2	MK3	WK 4	WK 5	WK 6	•••	WK 51	WK 52
Product 1	γ -	У		У	Υ				
Product 2	у		у		У				У
Product 3	Υ		у		у	Υ			У
Product 4			Υ			У			
Product 5	Υ			Υ					
Product 6	Υ	у		у					
Product 100	Υ			У	Υ			Υ	

Promotion Type	In store
Promotional Price	\$19.00
Shelf Price	\$23.50
Discount	\$4.50
Margin	35%
Retailer Margin	33%
Min/Max Frequencies	13/26 Weeks
Min/Max Sell Price	\$12/20
Min/Max Promo Gap	2/6 Weeks

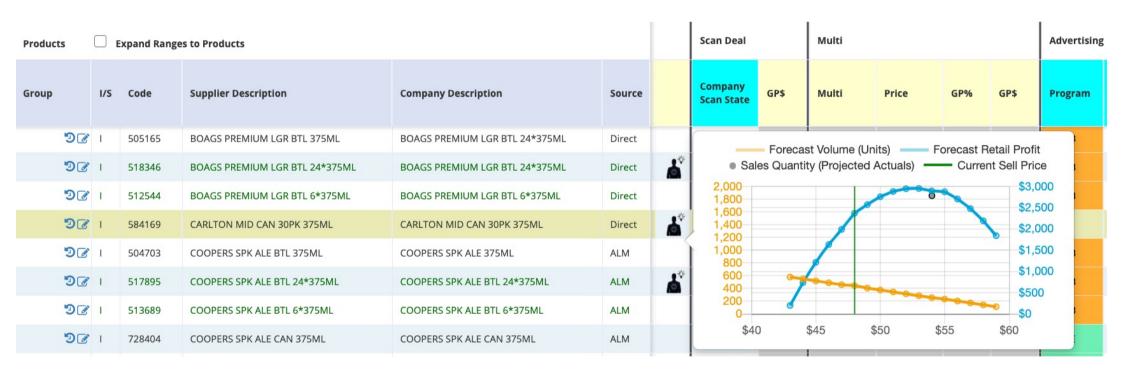








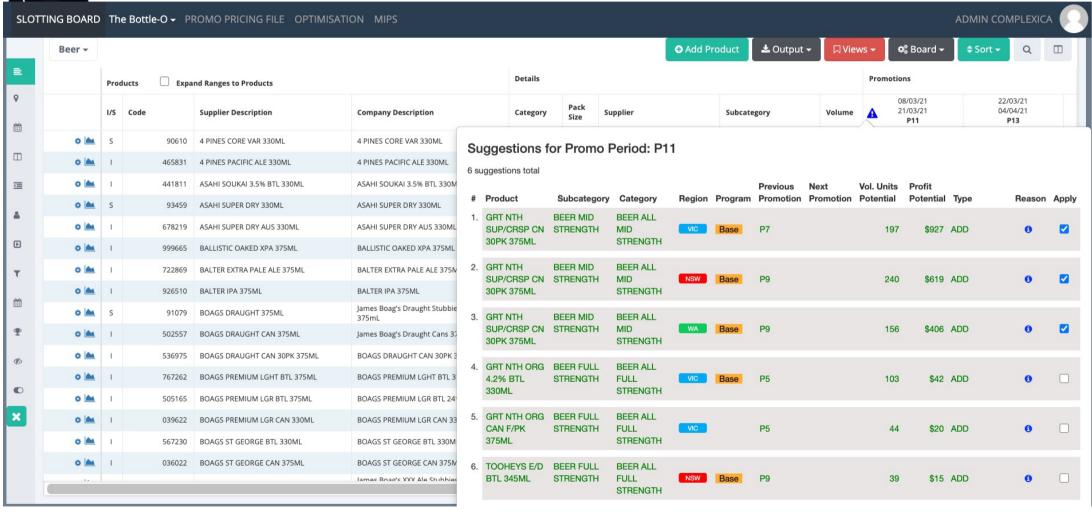
Discount Elasticities & Volume Predictions







Optimized Recommendations

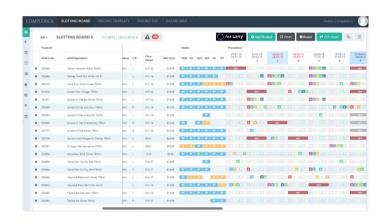




Predictive model should take into account:

- Promotion mechanics (e.g. two-for-one, % off)
- *Off-location* for the product
- Shelf price and discount of different products
- Catalogue entry (if any)
- *Price elasticity* of different products
- Pack-size cannibalization among products
- Sub-category cannibalization among products
- Cross-category cannibalization among products
- Delayed cannibalization
- Seasonality, including key selling periods
- Cross-retailer cannibalization



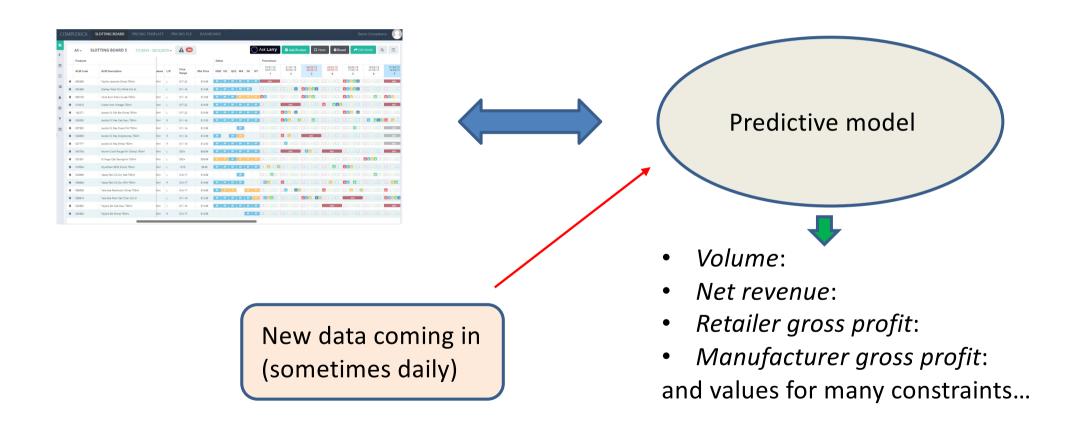




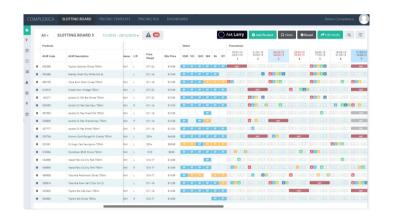
Predictive model

- Volume:
- Net revenue:
- Retailer gross profit:
- *Manufacturer gross profit*: and values for many constraints...

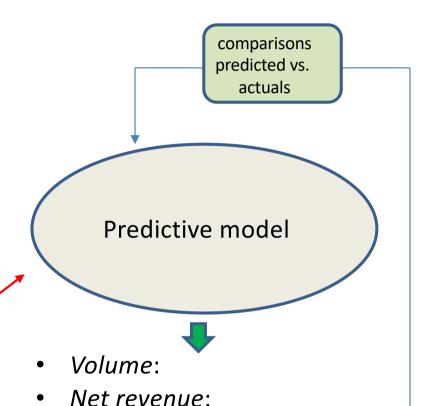








New data coming in (sometimes daily)



Retailer gross profit:

Manufacturer gross profit:

and values for many constraints...



Outline of the talk

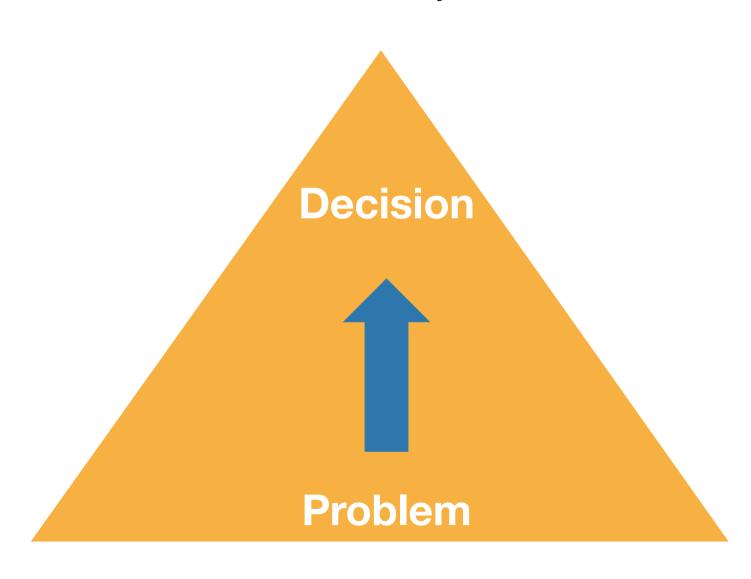
> 1999: NuTech Solutions

➤ 2005: SolveIT Software

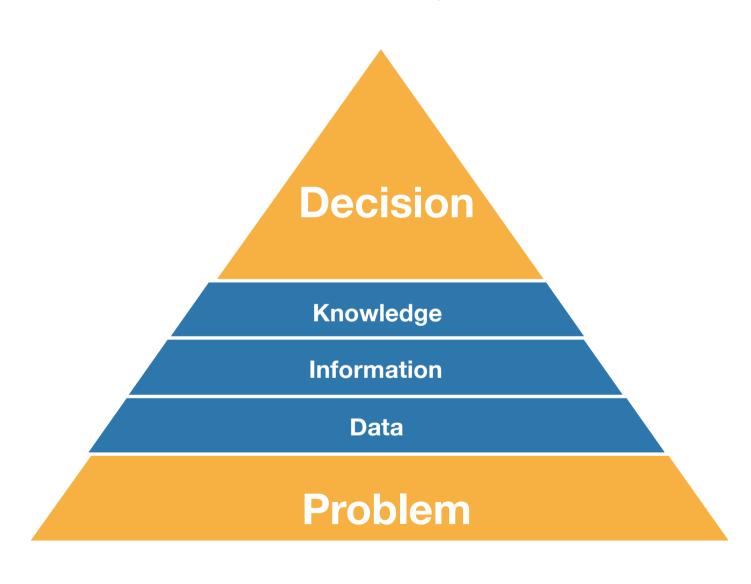
➤ 2014: Complexica

➤ Some thoughts on business applications and the EC research

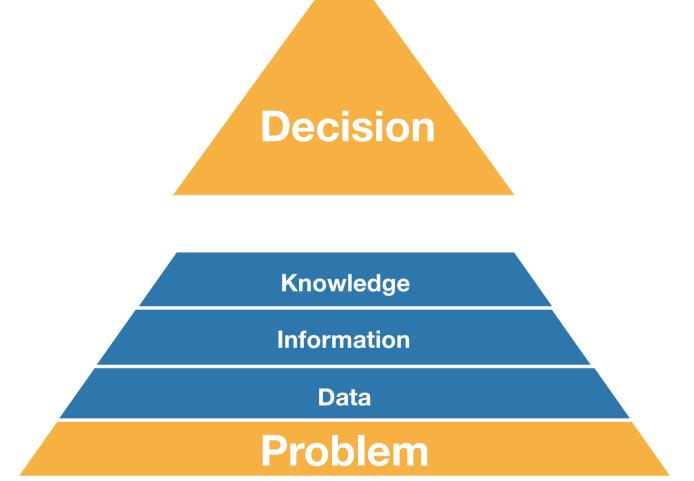




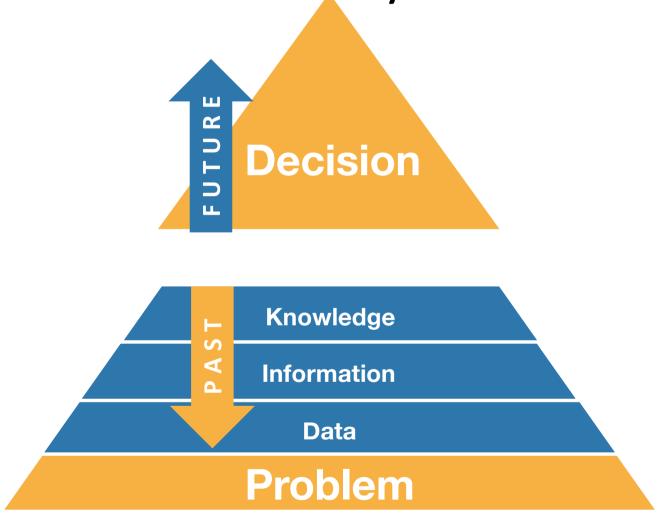




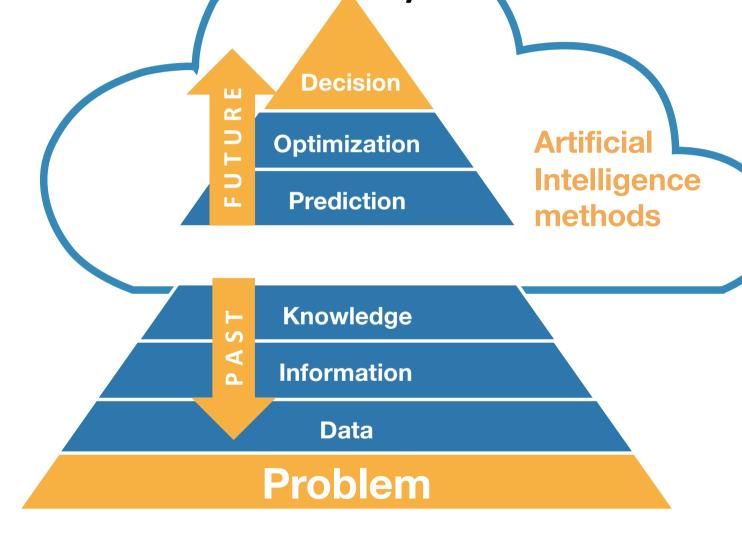




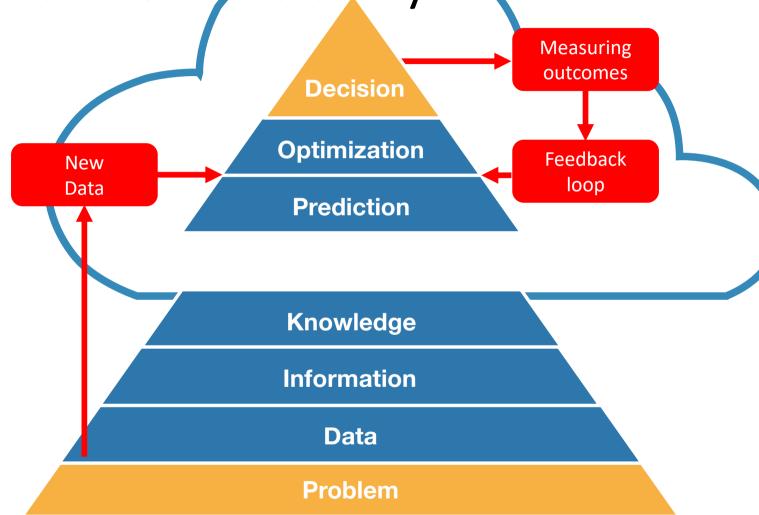








COMPLEXICA



COMPLEXICA

Some thoughts...

- 1) Continuous vs. discrete optimization problems
- 2) Single-objective vs. multi-objective problems
- 3) Global optimization; multi-component problems
- 4) Explanatory features of the optimizers
- 5) The nature of dynamic environments; the key importance of predictive models: their accuracy, updates, self-learning capabilities and some consequences



1) Continuous vs. discrete optimization problems



2) Single-objective vs. multi-objective problems

Most optimization-oriented business applications have several objectives...

However, it seems that the most meaningful arrangement for the end-user is to create a scenario, where one leading objective is defined, and other objectives are converted into constraints (thresholds), resulting in a "scenario" that is investigated.

A Scenario

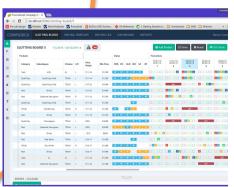
Input

| Companies | Comp

COMPLEXICA

Targe	Name	Current Plan	New Value			
V Jlume						
	Minimum Volume Outcome (Litres)	12,000				
	Minimum Volume Growth on Last Year (%)	10	5			
	Minimum Volume Share Outcome in Market (%)	15	20			
Net Sa	ales Revenue (NSR)					
	Minimum NSR Outcome (\$)	3,000	2,500			
	Minimum NSR Growth on Last Year (%)	12				
	Minimum NSR CPL (%)	10	10			
Cu.to	Cu. tomer Margin					
	Minimum Customer Margin \$	5,000				
	Maximum Customer Growth on Last Year (%)	10	5			
	Minimem Customer Margin (%)	10				
	Minimum GM CFL (%)	5	4			
Maxin	num Number of Changes		10			

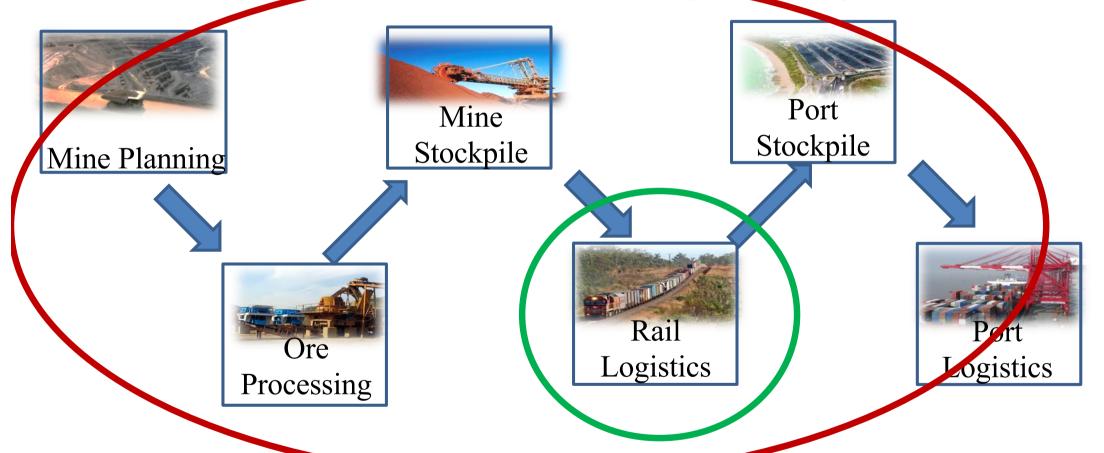




Output



3) Global optimization; multi-component problems



Local optimization

Global optimization



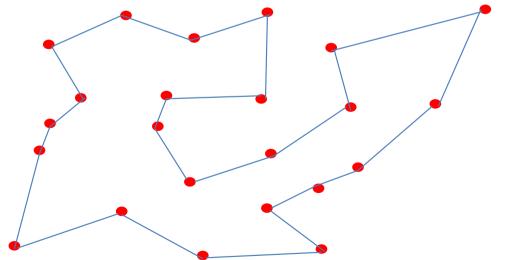
An article ©

Bonyadi, M.R., Michalewicz, Z., and Barone, L., *Travelling Thief Problem: the first step in transition from theoretical problems to realistic problems*, Proceedings of the 2013 IEEE Congress on Evolutionary Computation, Cancun, Mexico, June 20 - 23, 2013.



Travelling salesman problem

Given a list of cities and all costs of moving between them, find a cycle that visits each city precisely once and minimizes the total cost...



- ➤ Thousands of research papers
- ➤ Many books
- > Hundreds of algorithms
- ➤ Very active research area



Knapsack problem

Given a list of items, each with a value V and a weight W, select a number of items to maximize the total value but not exceed the threshold weight (capacity).

Again:

- > Thousands of research papers
- Many books
- Hundreds of algorithms
- Very active research area...

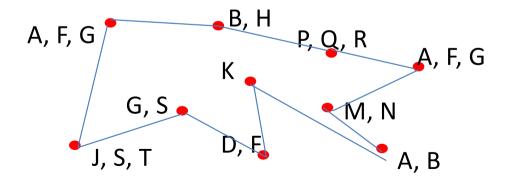


Travelling thief problem

Given a list of cities and items available in these cities, find a cycle that visits each city precisely once, collect some items available in these cities, to

- (1) minimize the total cost of the travel, and
- (2) maximize the value.

Note, that the cost of travel is a function of the current load...



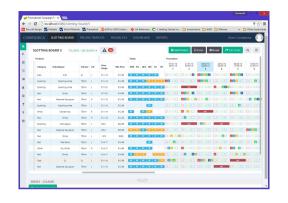


4) Explanatory feature of the optimizers and constraint-handling

Working on a variety of (academic) optimization problems I have never thought about any need to "justify" optimal solution that was found – simply because the evaluation score was "the best"...

However, this is not the case for business application – the end user needs to be convinced.... You hear very often: I would never do that the recommended way...

Target Name		Current Plan	New Value		
Volume					
	Minimum Volume Outcome (Litres)	12,000			
	Minimum Volume Growth on Last Year (%)	10	5		
	Minimum Volume Share Outcome in Market (%)	15	20		
Net S	Net Sales Revenue (NSR)				
	Minimum NSR Outcome (\$)	3,000	2,500		
	Minimum NSR Growth on Last Year (%)	12			
	Minimum NSR CPL (%)	10	10		
Customer Margin					
	Minimum Customer Margin \$	5,000			
	Minimum Customer Growth on Last Year (%)	10	5		
	Minimum Customer Margin (%)	10			
	Minimum GM CPL (%)	5	4		
Maxii	Maximum Number of Changes 10				





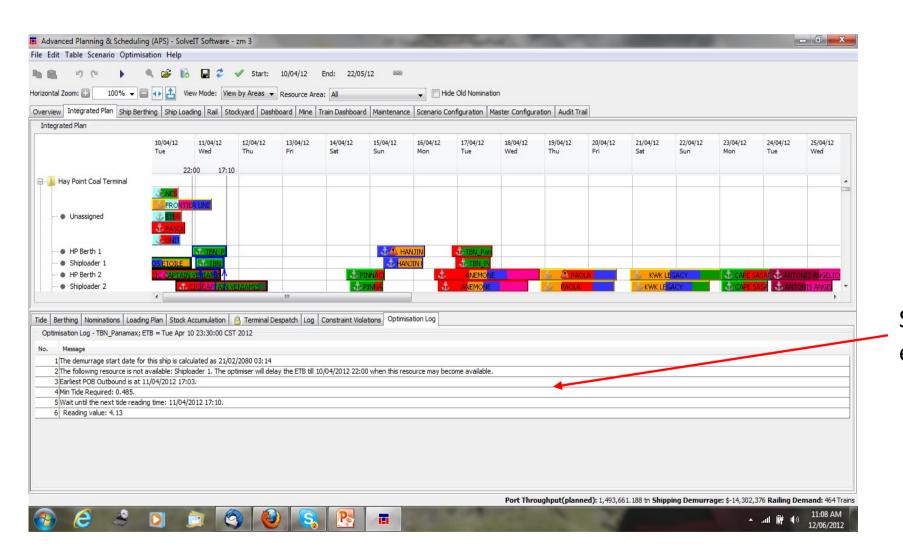
Very important!



4) Explanatory feature of the optimizers and constraint-handling

So, number of changes made to the initial solution might be useful.

Also, constraints could be used to justify the proposed solution:



Some explanations...



Additional comment on constraints:

Very often (always?) in a real-world optimization problem, the optimal solution lies on the boundary between feasible and infeasible areas of the search space...



Some papers from 25 years ago...

Schoenauer, M. and Michalewicz, Z., *Boundary Operators for Constrained Parameter Optimization Problems*, Proceedings of the 7th International Conference on Genetic Algorithms, East Lansing, Michigan, July 19 – 23, 1997, pp.320 – 329.

Schoenauer, M. and Michalewicz, Z., *Evolutionary Computation at the Edge of Feasibility*, Proceedings of the 4th Parallel Problem Solving from Nature, H.-M. Voigt, W. Ebeling, I. Rechenberg, and H.-P. Schwefel (Editors), September 22 – 27, 1996, Springer, Lecture Notes in Computer Science, Vol.1141, pp.245 – 254.



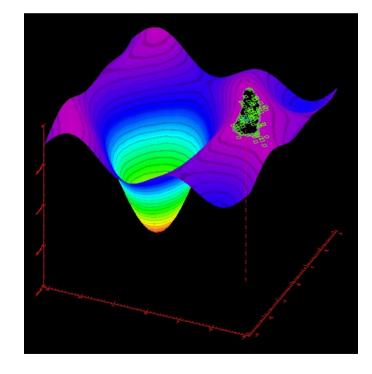
Additional comments on constraints:

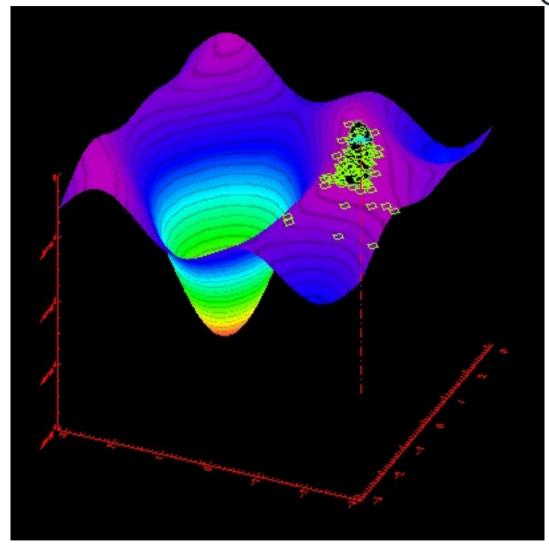
- ➤ Very often (always?) in a real-world optimization problem, the optimal solution lies on the boundary between feasible and infeasible areas of the search space...
- Classification of constraints into hard/soft represents a huge simplification
- ➤ Regardless whether a constraint is hard or soft, the users are interested what is a potential reward for violating it...
- > Constraints can be used for additional explanations...



5) The nature of dynamic environments; the key importance of predictive models: their accuracy, updates, self-learning

capabilities and some consequences









Predictive Model & Optimization

generate a solution check feasibility of the solution (constraints) evaluate the solution

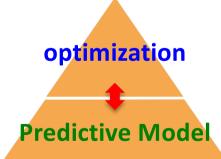
repeat

apply variation operator to the current solution to generate a new solution check feasibility of the new solution evaluate new solution

select one solution for further processing

end

report results







Predictive Model & optimization

generate a solution check feasibility of the solution (requires definitions of constraints) evaluate the solution

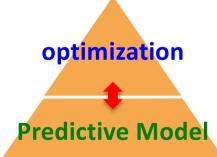
repeat

apply variation operator to the current solution to generate a new solution check feasibility of the new solution evaluate new solution

end

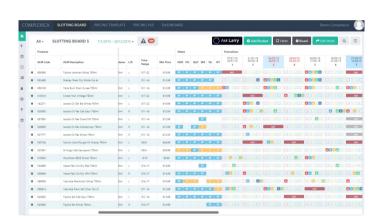
report results (e.g., trade-offs)

select one solution for further processing





Example: Promotional planning



New data coming in (sometimes daily)

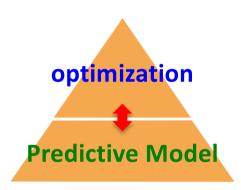
comparisons predicted vs. actuals

Predictive model

- Volume:
- Net revenue:
- Retailer gross profit:
- *Manufacturer gross profit*: and values for many constraints...



Some thoughts on development of a predictive model, its updates, feedback, learning, and adaptability



Understanding "dynamic environments"



time

Initial set of

data



STATIC ENVIRONMENT

Building, training, and testing the model...

time

Initial set of data



STATIC ENVIRONMENT

Building, training, and testing the model...

possibly with feedback loops and elements of learning

time

Initial set of data



STATIC ENVIRONMENT

Building, training, and testing the model...

possibly with feedback loops and elements of learning **OPERATING ENVIRONMENT (DYNAMIC)**

time

Initial set of data Point of deployment of the model (the model goes live)



STATIC ENVIRONMENT

Building, training, and testing the model...

possibly with feedback loops and elements of learning **OPERATING ENVIRONMENT (DYNAMIC)**

time

Initial set of data Point of deployment of the model (the model goes live) Initial set of data

New set of data



STATIC ENVIRONMENT

Building, training, and testing the model...

possibly with feedback loops and elements of learning **OPERATING ENVIRONMENT (DYNAMIC)**

time

Initial set of data Point of deployment of the model (the model goes live) Initial set of data New set of data (incremental activity; data arrive on regular basis)



STATIC ENVIRONMENT

Building, training, and testing the model...

... possibly with feedback loops and elements of learning

Initial set of data

OPERATING ENVIRONMENT (DYNAMIC)

Point of Initial deployment set of of the data model (the model

goes live)

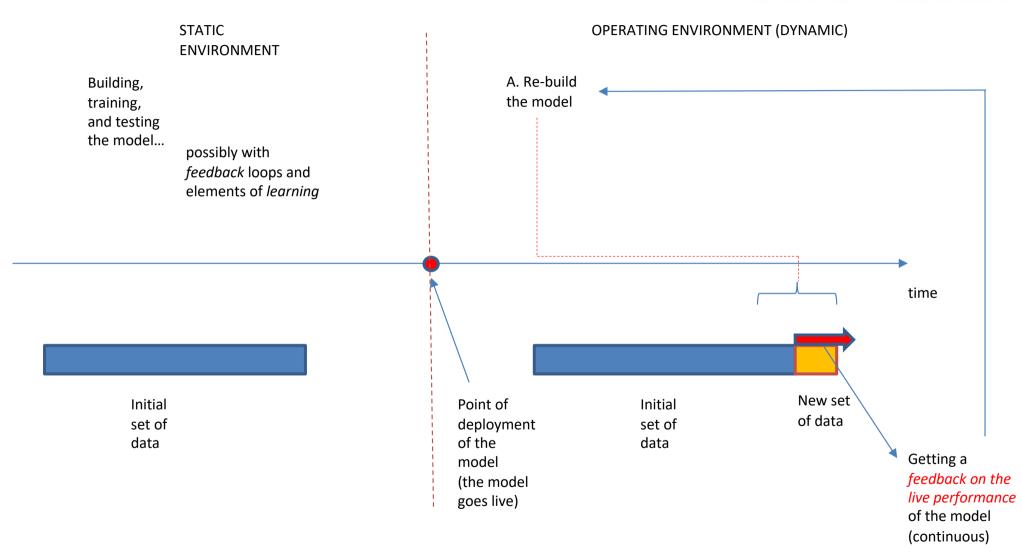
New set of data

Getting a

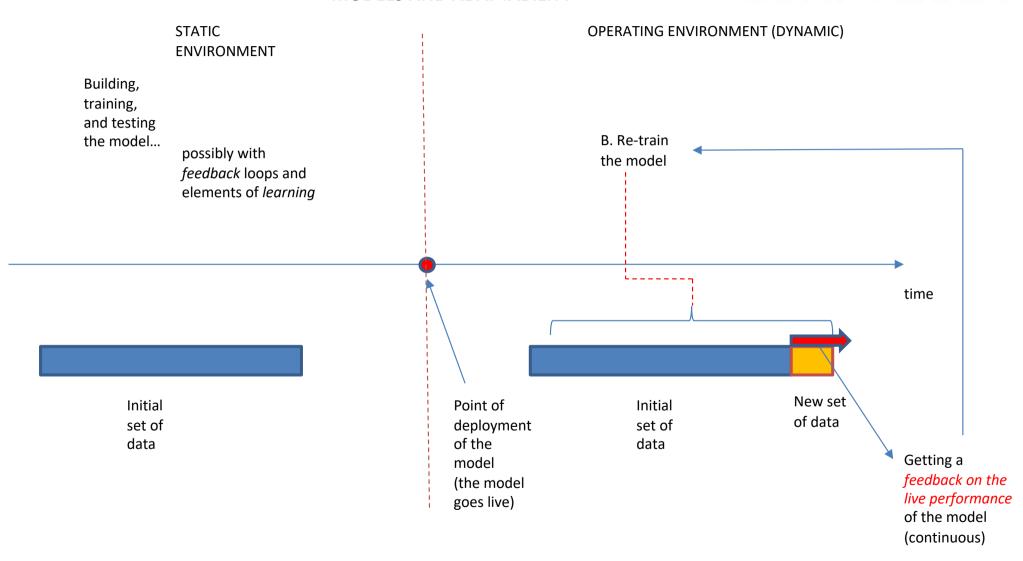
feedback on the
live performance
of the model
(continuous)

time

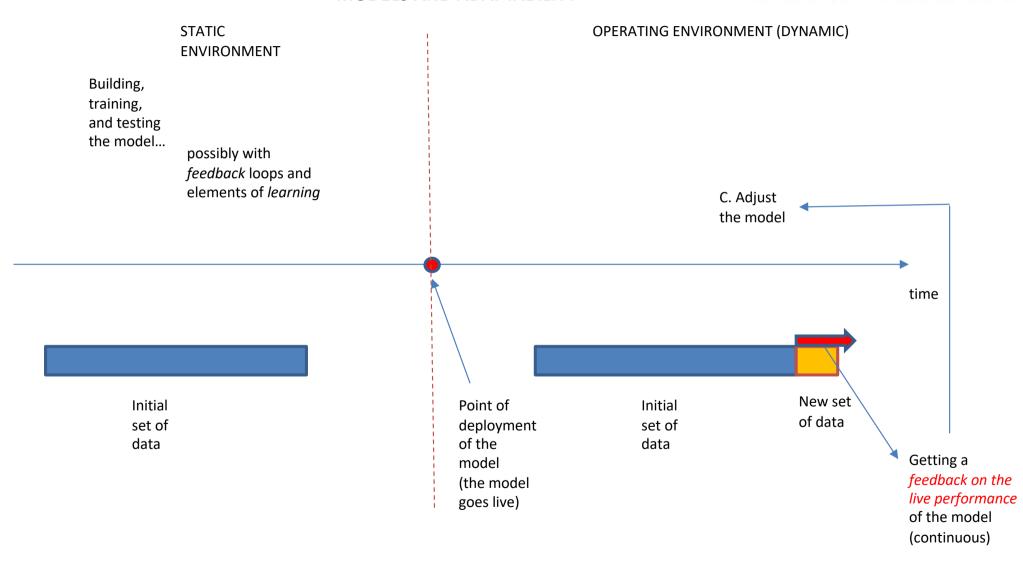




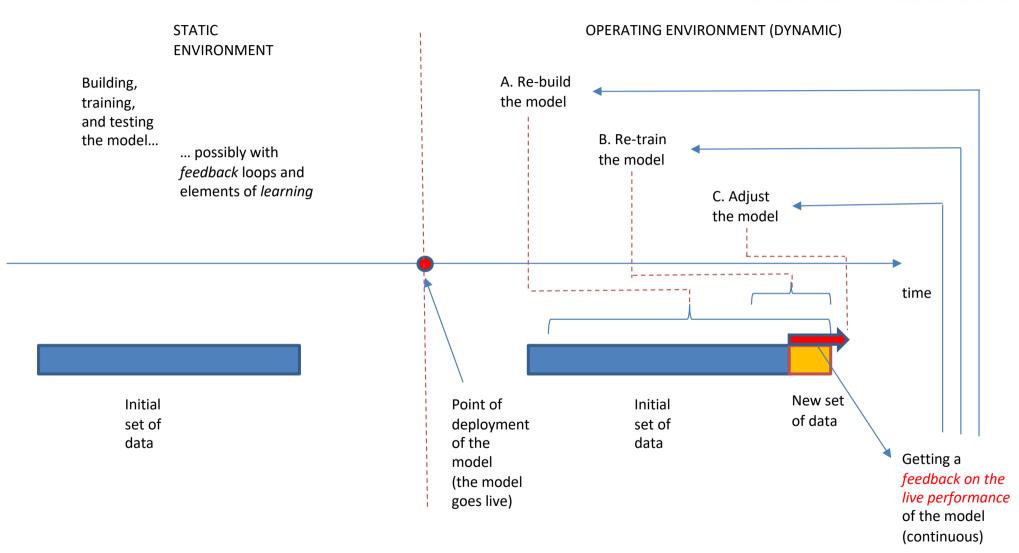




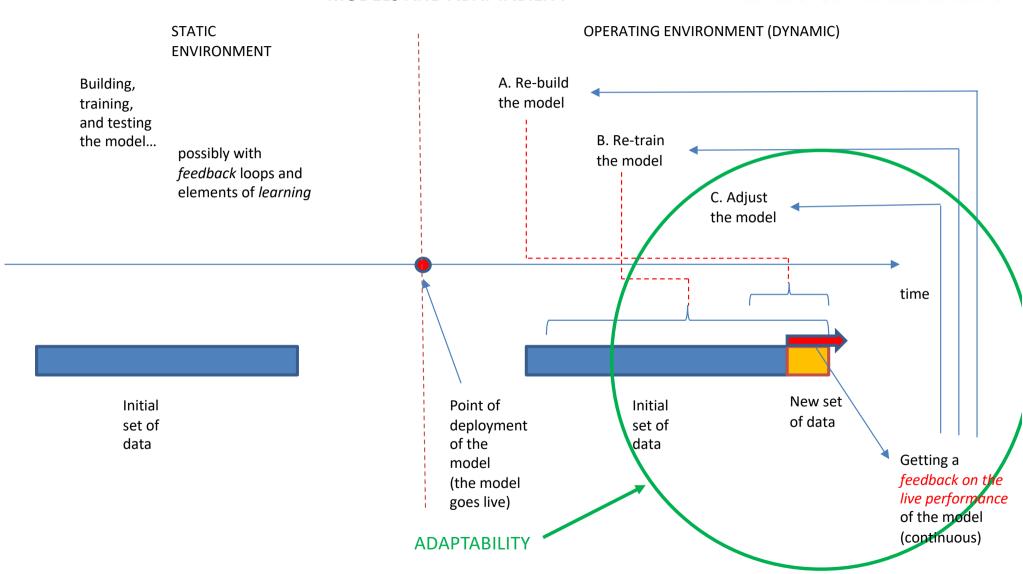












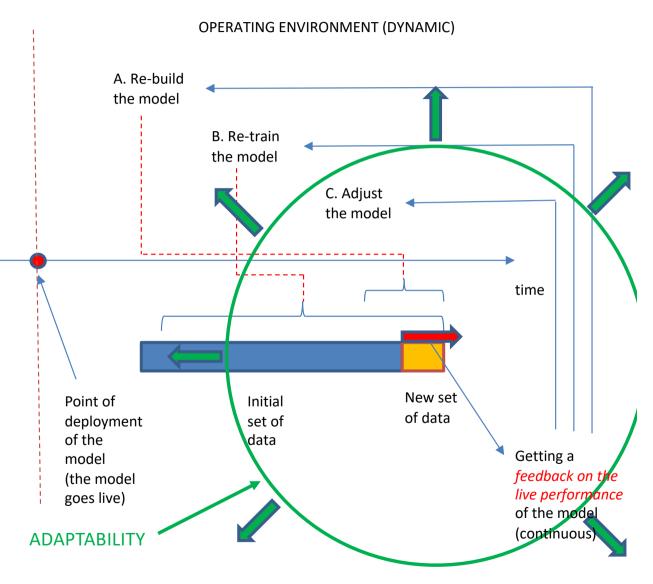


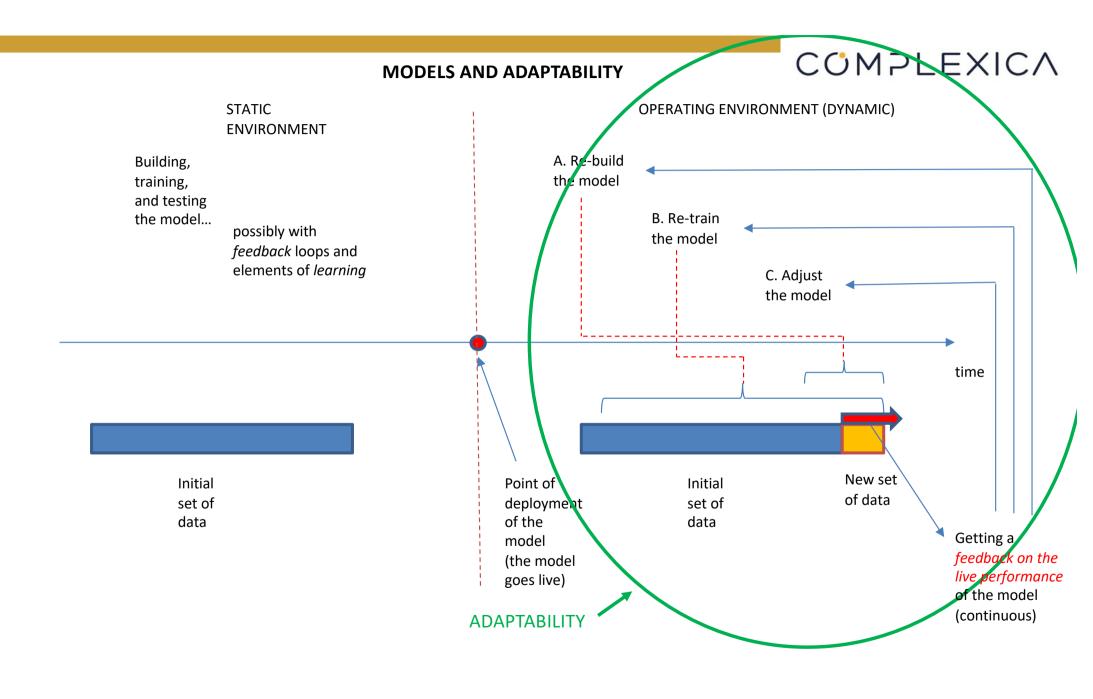


training, and testing the model...

possibly with feedback loops and elements of learning

Initial set of data





(continuous)

STATIC **ENVIRONMENT**

Building, training, and testing the model...

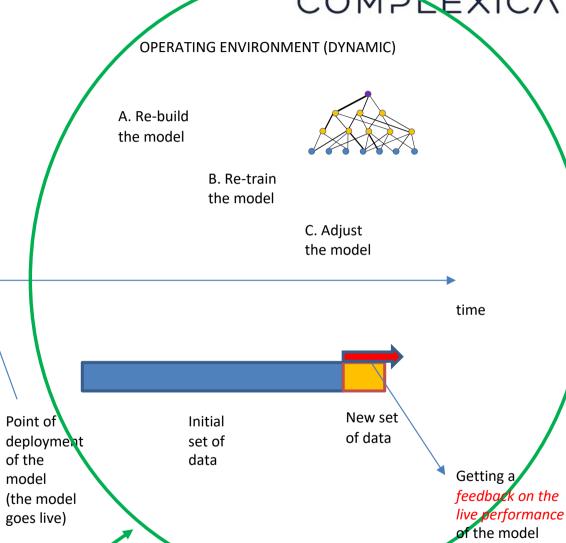
... possibly with feedback loops and elements of learning

of the

model

ADAPTABILITY

Initial set of data



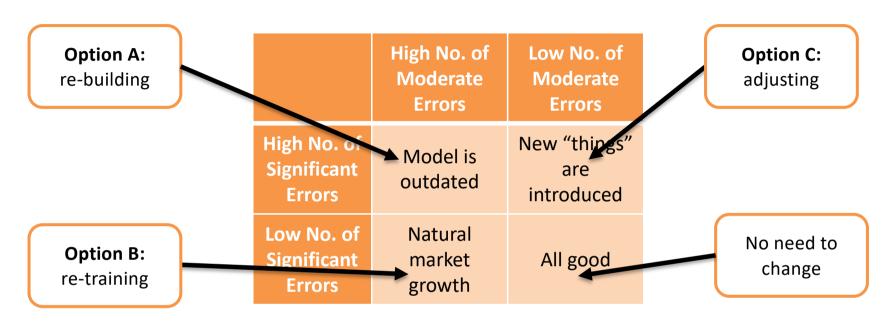


	High No. of Moderate Errors	Low No. of Moderate Errors
High No. of Significant Errors		
Low No. of Significant Errors		All good

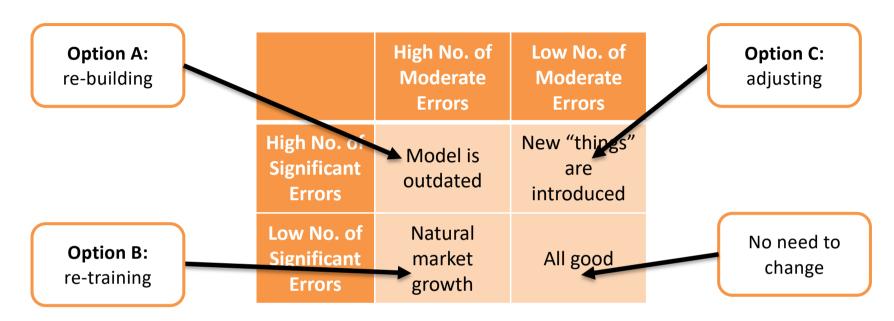


	High No. of Moderate Errors	Low No. of Moderate Errors
High No. of Significant Errors	Model is out-dated	New "things" are introduced
Low No. of Significant Errors	Natural market growth	All good

COMPLEXICA



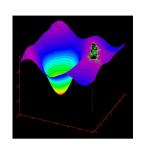
COMPLEXICA



- Option A: Re-building. Discard the old model, use all available data, old (possibly to some extend)
 and new, to re-build the model
- **Option B**: *Re-training*. Keep the old model, use all new data to train a separate (new) model. Both models (old and new) model work together (bagging strategy)
- **Option C**: Adapting. Keep the old model, use only the significant error cases to train a separate (new) model. Both models (old and new) work together (boosting strategy)



5) The nature of dynamic environments: predictive model as the evaluation function

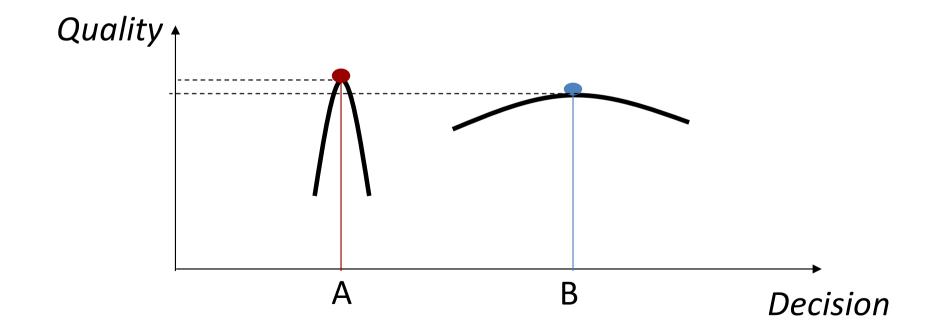


- How to handle updates: arrival of new data (on regular basis)?
- O How to handle the feedback on the accuracy of prediction?
- Opes the system learn?
- Should we forget the past? If yes, under what circumstances?
- Should we measure the dynamics of the environment?
- Should we introduce a mechanism by which the end user may influence the predictive model?



Variability and Risk

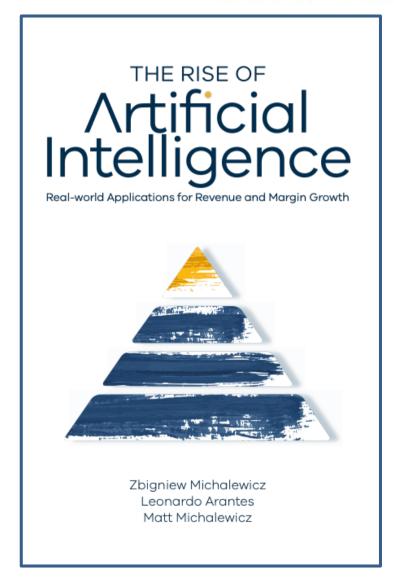
Without considering variability, some decisions will be "risker" than others





Additional information

The talk was based on my new book which was just published (April 2021)



Real World Problems vs. Research... COMPLEXICA

Adaptive Business Intelligence

Puzzle-based Learning

Constraint Handling Methods

Global Optimisation for Multi-component Problems

Partial Optimisation

Time Horizons, Variability, and Risk

Explanatory Features

Closing remarks

"Look at the last section [of some paper], where there were always some 'open problems.' Pick one, and work on it, until you are able to make a little progress. Then write a paper of your own about your progress, and don't forget to include an 'open problems' section, where you put in everything you were unable to do."

Jeff Ullman, 2009

Closing remarks

"Unfortunately this approach, still widely practiced today, encourages mediocrity. [...] It almost guarantees that after a while, the work is driven by what **can** be solved, rather than what **needs** to be solved."

"People write papers, and the papers get accepted because they are reviewed by the people who wrote the papers being improved incrementally, but the influence beyond the world of paper-writing is minimal."

Jeff Ullman, 2009

Two essays

- 1. Michalewicz, Z., *Quo Vadis, Evolutionary Computation? On a growing gap between theory and practice*, Springer LNCS State-of-the-Art Survey, J. Liu, C. Alippi, B. Bouchon-Meunier, G. Greenwood, H. Abbass (Editors), 2012.
- 2. Michalewicz, Z., *The Emperor is Naked: Evolutionary Algorithms for Real-World Applications*, ACM Ubiquity, November 2012, pp. 1 13.



Final observation...

"Luck plays a big role. Yes, I'd like to publicly acknowledge the power of luck. Athletes get lucky, poets get lucky, businesses get lucky. Hard work is critical, a good team is essential, brains and determination are invaluable, but luck may decide the outcome."

Phil Knight, Shoe Dog



Thank you...