Timing problems and vehicle routing

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- General effort dedicated to better address "rich vehicle routing problems" involving many side constraints and attributes.
- Observation : several VRP settings deserve their richness to the temporal features they involve : TW, time-dependent, flexible, break scheduling...
- The same questions faced in different domains: vehicle routing, scheduling, PERT, and so on.
- That led us to build a large cross-domain analysis and classification of *timing problems*.



- Several applications presenting similar *timing* issues
- Timing features and problems
 - Classification and notation
 - Reductions
- □ A timing feature example: soft time-windows
- Timing re-optimization































... with some characteristics in common





Timing problems

<u>TIMING</u>



- Timing problems seek to determine the execution dates (t₁,...,t_n) for a sequence of activities.
- Totally ordered continuous variables
- □ Additional *features* F^x characterized by functions f_y^x for $1 \le y \le m_x$ that participate either in the objective or as constraints:
 - time windows, time-dependent proc. times, flexible travel times, time lags, no waiting, limited waiting, and so on...



Timing problems

<u>TIMING</u>



- Several names in the literature: Scheduling, Timing, Projections onto Order Simplexes, Optimal service time problem ...
- Few dedicated studies, literature scattered among several research domains despite its relevance to many applications
- Thus motivating a dedicated review and analysis of timing algorithms to fill the gap.



Timing features from the vehicle routing domain

Rich vehicle routing problems can involve various *timing features*

\mathbf{Symbol}	Parameters	Char. functions	Most frequent roles		
D	due dates d_i	$f_i(\mathbf{t}) = (t_i - d_i)^+$	Service deadlines constraints, tardiness		
R	release dates r_i	$f_i(\mathbf{t}) = (r_i - t_i)^+$	Release-dates, earliness.		
TW	time windows	$f_i(\mathbf{t}) = (t_i - l_i)^+$	Time-window constraints,		
	$TW_i = [e_i, l_i]$	$+(e_i-t_i)^+$	soft time windows.		
MTW	multiple TW	$f_i(\mathbf{t}) = \min\left[(t_i - l_{ik})^+\right]$	Multiple time-window constraints		
	$MTW_i = \cup [e_{ik}, l_{ik}]$	$+(e_{ik}-t_i)^+]$			
$\Sigma c_i(t_i)$	general $c_i(t)$	$f_i(\mathbf{t}) = c_i(t_i)$	Time-dependent service costs		
$\Sigma c_i^{\text{CVX}}(t_i)$	convex $c_i^{\text{cvx}}(t_i)$	$f_i(\mathbf{t}) = c_i^{\text{cvx}}(t_i)$	Time-d. convex service costs		
DUR	total dur. δ_{max}	$f(\mathbf{t}) = (t_n - \delta_{max} - t_1)^+$	Duration or overall idle time		
NWT	no wait	$f_i(\mathbf{t}) = (t_{i+1} - p_i - t_i)^+$	No wait constraints		
IDL	idle time ι_i	$f_i(\mathbf{t}) = (t_{i+1} - p_i - \iota_i - t_i)^+$	Limited idle time per stop, min idle time		
			excess		
P(t)	time-dependent	$f_i(\mathbf{t}) = (t_i + p_i(t_i) - t_{i+1})^+$	Time-dependent driving-times		
	proc. times $p_i(t_i)$				
TL	time-lags δ_{ij}	$f_i(\mathbf{t}) = (t_j - \delta_{ij} - t_i)^+$	Time-lag constraints		
$\Sigma c_i(\Delta t_i)$	general $c_i(t)$	$f_i(\mathbf{t}) = c_i(t_{i+1} - t_i)$	Flexible travel times		
$\Sigma c_{ij}(t_i, t_j)$	general $c_{ij}(t,t')$	$f_{ij}(\mathbf{t}) = c_i(t_i, t_j)$	Separable objectives or constraints by any		
0.07	U ~ <i>P</i>		pairs of variables		



Timing features hierarchy

- These features can be classified and hierarchized (many-one linear reduction relationships between the associated timing problems)
- Features in the NP hard area lead to NP hard timing problems





Timing features hierarchy

- In this presentation,
 brief glimpse of the analysis.
- We examine a particular feature as illustrative example
- A similar study has been conducted on other features from this figure.





- Timing problem
 - with soft time-windows (penalized early and late arrival)
 - and generally with any convex separable cost

$$\min_{\substack{(t_1, \dots, t_n) \in \Re^{n+} \\ s.t.}} \sum_{i=1}^n \{ \alpha (\bar{e_i} - t_i)^+ + \beta (t_i - \bar{l_i})^+ \}$$

$$s.t. \quad t_i + p_i \le t_{i+1} \qquad 1 \le i < n$$

$$\begin{array}{c|c} \min_{(t_1,\ldots,t_n)\in\Re^n} & \sum_{i=1}^n c_i^{\text{CVX}}(t_i) \\ s.t. & t_i + p_i \le t_{i+1} \end{array}$$

- We inventoried more than 30 algorithms from various domains (routing, scheduling, PERT, statistics...) that address these models.
- The solution block representation / active set framework (Chakravarti 1989, Best & Chakravarti 1990, Best et al. 2000, Ahuja & Orlin 2001) can be used to characterize these methods. But we need to generalize the optimality conditions to the non-smooth case.



- □ A block B is defined as a subsequence of activities $(a_{B(1)}, ..., a_{B(|B|)})$ processed consecutively (such that $t_i + p_i = t_{i+1}$)
- □ <u>Theorem (Generalization of Best & Chakravarti 1990)</u>: Let costs $c_i(t_i)$ be proper convex, eventually nonsmooth, functions. A solution $(t_1^*,...,t_n^*)$ of the timing problem with convex separable costs is optimal if and only if it can be assimilated to a succession of activity blocks $(B_1,...,B_m)$ such that:
 - 1) Blocks are optimally placed: for each block B_i , $t^*_{Bi(1)} \in argmin C_{Bi}(t)$
 - 2) Blocks are spaced: for each pair of blocks (B_i, B_{i+1}) , $t^*_{B_i(1)} + \sum_{i} p_{B_i(j)} < t^*_{B_{i+1}(1)}$
 - 3) **Blocks are consistent**: for each block B_i and prefix block B_i^k,

max argmin $C_{Bi}^{k}(t) \ge t_{Bi(1)}^{*}$









- □ Three main families of algorithms can be identified:
 - Primal feasible, that respect spacing condition 2
 - > Dual feasible, that respect *consistency condition 3*
 - > Dynamic programming
- □ To illustrate, consider this small problem with 6 activities





Primal feasible method, respecting the spacing condition.

- > Brunk (1955) : Minimum Lower Set Algorithm in O(n²) unimodal minimizations.
- Extended by Garey et al. (1988) and Best & Chakravarti (1990) to work, respectively, in O(n log n) elementary operations in the case of (E/T) scheduling, and O(n) unimodal function minimizations in the general convex case.



Garey et al. (1988)

Best & Chakravarti (1990)

- > Several other related methods designed for (E/T) scheduling
- > In the context of PERT with convex costs : Chrétienne and Sourd (2003)



Dual feasible method, respecting the consistency condition.

> Ayer et al. (1955) : Pool Adjacent Violator Algorithm (PAV).



- Extended to the general convex case by Best et al. 2000 and Ahuja & Orlin (2001) -> O(n) function minimizations
- Can work in O(n log² n) for Isotone Regression with || ||₁ (equivalent to (E/T) with equal penalties for earliness and tardiness) (Pardalos 1995)
- For the VRP with convex service costs, Dumas et al. 1990 can be viewed as another application of this principle



- Dynamic programming-based methods (Yano and Kim 1991, Sourd 2005, Ibaraki et al. 2005, 2008, Hendel and Sourd 2007, Hashimoto et al. 2006, 2008)
- Forward dynamic programming

$$F_i(t) = \min_{0 \le x \le t} \{ c_i(x) + F_{i-1}(x - p_{i-1}) \}$$

□ Backward dynamic programming

$$B_i(t) = \min_{x \ge t} \{ c_i(x) + B_{i+1}(x+p_i) \}$$



 Hence, many different methods for this particular feature example. The literature on timing problems is rich, but scattered. All in all, 26 different methods from different domains were classified as variations of 3 main algorithmic ideas.



- Furthermore, when used within LS, solving all timing problems *from* scratch is generally not efficient
- □ General goal when exploring neighborhoods: solving series of timing problems on several activity permutations $\sigma \in N$.

$$\min_{\mathbf{t}=(t_1,\dots,t_n)\in\Re^{n+}} \sum_{F^x\in\mathcal{F}^{\text{OBJ}}} \alpha_x \sum_{1\leq y\leq m_x} f_y^x(\mathbf{t})$$
s.t. $t_{\sigma^k(i)} + p_{\sigma^k(i)\sigma^k(i+1)} \leq t_{\sigma^k(i+1)}$
 $f_y^x(\mathbf{t}) \leq 0$



- □ In classical VRP neighborhoods, the neighborhood size is often rather large: $|N| = \Omega(n^2)$, and permutations are very particular.
 - > They have a bounded number (often <= 4) of *breakpoints:* integers x such that $\sigma(x)+1 \neq \sigma(x+1)$,

The resulting sequences of activities can be assimilated to a recombination of a small number of subsequences.

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Timing re-optimization

- Efficient *timing re-optimization* by means of a subset of 4 procedures, used within local searches:
 - > Initialization of suitable re-optimization data for a single activity
 - Forward (F) or backward (B) computation of data on larger subsequences
 - Evaluation of a concatenation of two (C2) or more (C3+) subsequences

Algorithm 1 Re-optimization

- 1: Build re-optimization data on subsequences of the *incumbent timing problem* \mathcal{T} , using *initialize*, and *forward extension* or *backward extension*.
- 2: For each timing subproblem \mathcal{T}^k , $k \in \{1, \ldots, N\}$;
- 3: Determine the breakpoints involved in the permutation function σ^k ;
- 4: Evaluate the optimal cost of \mathcal{T}^k , as the concatenation of $b(\sigma) + 1$ activity subsequences from \mathcal{T} (see Equation 39).



Example of soft time-windows: Forward and backward extension to compute data on subsequences, and *evaluate concatenation* of 2 sequences (Ibaraki et al. 2005, 2008):

$$Z^*(A_1 \oplus A_2) = \min_{t \ge 0} \{ F(A_1)(t) + B(A_2)(t + p_{A_1(|A_1|)A_2(1)}) \}$$

- In the convex case, the concatenation of 3+ sequences is also addressed efficiently.
- > O(log ϕ) for convex piecewise functions with a total of ϕ pieces.
- > O(log n) move evaluations for soft TW



- For other features: Surveying the literature, we classified many reoptimization based methodologies from various domains, and for a large variety of attributes. (Savelsbergh 1985,1992, Kindervater and Savelsbergh 1997, Campbell and Savelsbergh 2004, Ergun and Orlin 2006, Irnich 2008, Hashimoto et al. 2006,2008, Kedad-Sidhoum and Sourd 2010)...
- We could identify a set of state-of-the-art timing methods, which are the key to solve many rich VRP settings:



Conclusions of this analysis

Problem	From Scra	tch	Re-opt. by concat.	F/B C2	C3+	\mathbf{Sd}	Assumptions
$\{W \phi\}$	Min idle time	O(n)		O(1)	O(1)	\checkmark	
$\{ \phi TW \}$	Min idle time	O(n)	Savelsbergh (1985) & Kind. and Sav. (1997)	O(1)	O(1)	~	
$\{D \phi\}$	Min idle time	O(n)	Ergun and Orlin (2006)	$O(\log n) O(1)^*$	—		penalty coefficient depending upon act.
$\{D, R(d_i = r_i) NWT\}$	Min idle time	O(n)	Kedad-Sidhoum and Sourd (2010)	$O(\log n) O(1)^*$	—		penalty coefficient depending upon act.
$\{D, R(d_i = r_i) \phi\}$	Garey et al. (1988) & Ahuja and Orlin (2001)	$O(n\log n)$	Ibaraki et al. (2008)	$O(\log n)$	$O(\log n)$	~	
$\{D R\}$	Min idle time	O(n)	Ibaraki et al. (2008)	$O(\log n)$	$O(\log n)$	\checkmark	
$\{\Sigma c_i^{ ext{cvx}}(t_i) extsf{ extsf{ iny opt}}\}$	Ibaraki et al. (2008)	$O(n\log arphi_c)$	Ibaraki et al. (2008)	$O(\log arphi_c)$	$O(\log arphi_c)$	\checkmark	cost f. $\geq 0,$ p.l. & l.s.c
$\{\Sigma c_i(t_i) { m eta}\}$	Ibaraki et al. (2005)	$O(n arphi_c)$	Ibaraki et al. (2005)	$O(arphi_c)$	$O(arphi_c)$	\checkmark	cost f. $\geq 0,$ p.l. & l.s.c
$\{\phi MTW\}$	Min idle time	$O(n + \varphi_{\text{mtw}})$	Ibaraki et al. (2005)	$O(\log \varphi_{\scriptscriptstyle \mathrm{MTW}})$	_	\checkmark	
$ \{ DUR TW \}, \\ \{ \phi DUR, TW \} $	Malcolm et al. (1959)	O(n)	Savelsbergh (1992) & Kind. and Sav. (1997)	O(1)	O(1)	~	
$ \{ DUR MTW \}, \\ \{ \phi DUR, MTW \} $	Tricoire et al. (2010)	$O(n arphi_{MTW})$	Hashimoto et al. (2006)	$O(arphi_{ ext{mtw}})$	—	~	
$\{ \emptyset IDL, TW \}$	Hunsaker and S. (2002)	O(n)			_		
$\{\Sigma c_i^{\scriptscriptstyle ext{\tiny CVX}}(\Delta t_i), \Sigma c_i(t_i) extsf{ extsf{ iny boundary constraint}}\}$	Sourd (2005) & Hashimoto et al. (2006)	$O(n(\varphi_c + \widehat{\varphi_c} \times \varphi_c'))$	Sourd (2005) & Hashimoto et al. (2006)	$O(\varphi_c + \widehat{\varphi_c} \times \varphi_c')$	—	~	cost f. $\geq 0,$ p.l. & l.s.c
$\{D R, P(t)\}$	Min idle time	O(n)					FIFO assumption
$\{ \phi TW, P(t) \}$	Donati et al. (2008)	O(n)	Donati et al. (2008)	O(1)		\checkmark	FIFO assumption
$\{\Sigma c_i(t_i) P(t)\}$	Hashimoto et al. (2008)	$O(n(arphi_c+arphi_p))$	Hashimoto et al. (2008)	$O(arphi_c+arphi_p)$	_	~	cost f. ≥ 0 , p.l. & l.s.c & HYI assumption
$\{ \phi TL, TW \}$	Hurink and Keuchel (2001)	$O(n^3)$			_		
$\{ \phi TL, TW \}$	Haugland and Ho (2010)	$O(n \log n)$			_		O(n) TL constraints
$\{DUR > D > TL R\}$	Cordeau and Laporte (2003)	$O(n^2)$	_		_		O(n) TL constraints & LIFO assumption
$\{ \Sigma c_{ij}^{ ext{cvx}}(t_j - t_i), \Sigma c_i^{ ext{cvx}}(t_i) ext{ extsf{ iny boundary constraint}} \}$	Ahuja et al. (2003)	$O(n^3 \log n \log(nU))$	_		_		U is an upper bound of execution dates





Conclusions of this analysis

- Large analysis of a rich body of problems with time characteristics and totally ordered variables. Cross-domain synthesis, considering methods from various fields such as vehicle routing, scheduling, PERT, and isotonic regression. Identification of main resolution principles
- For several "rich" combinatorial optimization settings, the timing subproblems represent the core of "richness" and deserve particular attention.
- Furthermore, timing sub-problems frequently arise in the context of local search, and thus we analyzed both stand-alone resolution and efficient solving of series of problems.



- Timing procedures are being integrated in a recent efficient Hybrid Genetic Search with Advanced Diversity Control (HGSADC- Vidal et al. 2011), opening the way to a new generalist solver for rich VRPs with timing features.
- Several features and feature combinations were identified in this work, for which new timing algorithms (including re-optimization procedures) should be sought.
- Generalization to other cumulative resources, multi-objective or stochastic settings.
- □ More studies on complexity lower bounds.



- □ For further reading : <u>A unifying view on timing problems and</u> algorithms (2011), CIRRELT-43-2011, Technical Report.
- □ Thanks a lot for your attention



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