# Appendix for Domain-Independent Dynamic Programming: Generic State Space Search for Combinatorial Optimization* 

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## CP Models

We present the new CP models used in the experimental evaluation.

## TSPTW

We adapt a CP model for a single machine scheduling problem with time windows (Booth et al. 2016) to TSPTW. Let $x_{i}$ be an interval variable in a range $\left[a_{i}, b_{i}\right]$ with the length of 0 , representing visiting customer $i$.

$$
\begin{array}{ll}
\min & \sum_{i \in N} c_{i, \operatorname{Next}\left(x_{i}\right)} \\
\text { s.t. } & \operatorname{NoOverlap}\left(\left[x_{0}, \ldots, x_{n-1}\right],\left\{c_{i j} \mid i, j \in N\right\}\right) \\
& \text { First }\left(x_{0}\right) \\
& x_{i}: \text { intervalVar }\left(0,\left[a_{i}, b_{i}\right]\right)
\end{array} \forall i \in N .
$$

The first constraint ensures that interval variables are ordered in a sequence, and for two consecutive variables $x_{i}$ and $x_{j}$, the start of $x_{j}$ must be at least $c_{i j}$ greater than the end of $x_{i}$. In the objective, $\operatorname{Next}\left(x_{i}\right)$ is the interval variable next to $x_{i}$ in the sequence. For the last variable, we let $\operatorname{Next}\left(x_{i}\right)=x_{0}$. The second constraint ensures that the depot is visited first.

## SALBP-1

For SALBP-1, we implement the CP model proposed by Bukchin and Raviv (2018) with the addition of the Pack global constraint (Shaw 2004). For an upper bound on the number of stations, instead of using a heuristic to compute it, we use $\bar{m}=\min \left\{n, 2\left\lceil\sum_{i \in N} t_{i} / c\right\rceil\right\}$ following the MIP model (Ritt and Costa 2018). Let $M=\{0, \ldots, \bar{m}-1\}$ be the set of stations. Let $m$ be a decision variable representing the number of stations, $x_{i}$ be a decision variable representing the index of the station of task $i$, and $y_{j}$ be the sum of the processing times of tasks scheduled in station $j$. The set of all direct and indirect predecessors of task $i$ is

$$
\tilde{P}_{i}=\left\{j \in N \mid j \in P_{i} \vee \exists k \in \tilde{P}_{j}, j \in \tilde{P}_{k}\right\} .
$$

The set of all direct and indirect successors of task $i$ is

$$
\tilde{S}_{i}=\left\{j \in N \mid i \in P_{j} \vee \exists k \in \tilde{S}_{i}, j \in \tilde{S}_{k}\right\}
$$

[^0]Thus,

$$
e_{i}=\left\lceil\frac{t_{i}+\sum_{k \in \tilde{P}_{i}} t_{k}}{c}\right\rceil
$$

is a lower bound on the number of stations required to schedule task $i$,

$$
l_{i}=\left\lfloor\frac{t_{i}-1+\sum_{k \in \tilde{S}_{i}} t_{k}}{c}\right\rfloor
$$

is a lower bound on the number of stations between the station of task $i$ and the last station, and

$$
d_{i j}=\left\lfloor\frac{t_{i}+t_{j}-1+\sum_{k \in \tilde{S}_{i} \cap \tilde{P}_{j}} t_{k}}{c}\right\rfloor
$$

is a lower bound on the number of stations between the stations of tasks $i$ and $j$.

$$
\begin{array}{lr}
\min & m \\
\text { s.t. } \operatorname{Pack}\left(\left\{y_{j} \mid j \in M\right\},\left\{x_{i} \mid i \in N\right\},\left\{t_{i} \mid\right.\right. & i \in N\}) \\
& 0 \leq y_{j} \leq c \\
& \quad \forall j \in M \\
e_{i}-1 \leq x_{i} \leq m-1-l_{i} & \forall i \in N \\
& x_{i}+d_{i j} \leq x_{j} \quad \forall j \in N, \forall i \in \tilde{P}_{j}, \\
& \\
& \\
m \in \mathbb{Z} & \nexists k \in \tilde{S}_{i} \cap \tilde{P}_{j}: d_{i j} \leq d_{i k}+d_{k j} \\
y_{j} \in \mathbb{Z} & \forall j \in M \\
x_{i} \in \mathbb{Z} & \forall i \in N .
\end{array}
$$

The first constraint ensures $x_{i} \in M$ and $\sum_{i \in N: x_{i}=j} t_{i}=y_{j}$. The second constraint ensures that the sum of the processing times does not exceed the cycle time. The third constraint states the lower and upper bounds on the index of the station of $i$. The fourth constraint is an enhanced version of the precedence constraint using $d_{i j}$.

## Bin Packing

For the CP model for bin packing, we also use Pack. In addition, we ensure that item $i$ is packed in the $i$-th or an earlier
bin.

$$
\begin{array}{lr}
\min \max _{i \in N} x_{i}+1 & \\
\text { s.t. } \operatorname{Pack}\left(\left\{y_{j} \mid j \in M\right\},\left\{x_{i} \mid i \in N\right\},\left\{t_{i} \mid i \in N\right\}\right) \\
0 \leq y_{j} \leq c & \forall j \in M \\
0 \leq x_{i} \leq i & \forall i \in N \\
y_{j} \in \mathbb{Z} & \forall j \in M \\
x_{i} \in \mathbb{Z} & \forall i \in N .
\end{array}
$$

We compute the upper bound $\bar{m}$ using the first-fit decreasing heuristic.

## DP Models

We prove the properties of the DP models assumed in the paper and provide the DyPDL representations of the models.

## Lower Bounds for SALBP-1 and Bin Packing

We show that the lower bounds used in the DP models for SALBP-1 and bin packing are valid. These lower bounds, LB1, LB2, and LB3 were originally proposed by Scholl and Klein (1997). The first lower bound, LB1, is originally defined as $\left\lceil\sum_{i \in N} t_{i} / c\right\rceil$. This bound relaxes the problem by allowing to split a task across multiple stations. In a state $\langle U, r\rangle$ ( $\langle U, r, k\rangle$ for bin packing), we only need to schedule tasks in $U$, and we can schedule tasks in the current station, which has the remaining time of $r$. Therefore, we use $\left\lceil\left(\sum_{i \in U} t_{i}-r\right) / c\right\rceil$ as a lower bound.

The second lower bound, LB2, is originally defined as $\sum_{i \in N} w_{i}^{2}+\left\lceil\sum_{i \in N} w_{i}^{\prime 2}\right\rceil$, where $w_{i}^{2}=1$ if $t_{i}>c / 2$ and $w_{i}^{\prime 2}=1 / 2$ if $t_{i}=c / 2$. This bound only considers tasks $i$ with $t_{i} \geq 2 / c$. The first term, the number of tasks $i$ with $t_{i}>2 / c$, is a lower bound because other tasks cannot be scheduled in the same station as $i$. For the remaining tasks, which have $t_{i}=2 / c$, two tasks can be scheduled in the same station, which results in the second term. In our model, in a state $\langle U, r\rangle$, we use the bound $\sum_{i \in U} w_{i}^{2}+\left\lceil\sum_{i \in U} w_{i}^{\prime 2}\right\rceil$ if $r<c / 2$ because we cannot schedule any tasks with $t_{i} \geq 2 / c$ in the current station. If $r \geq c / 2$, since we may use the current station, we subtract 1 from the bound.

The second lower bound, LB3, is based on a similar idea to LB2. It is originally defined as $\left\lceil\sum_{i \in N} w_{i}^{\prime 3}\right\rceil$ and only considers tasks $i$ with $t_{i} \geq 3 / c$. Therefore, we use the bound $\left\lceil\sum_{i \in U} w_{i}^{3}\right\rceil$ if $r<c / 3$ and subtract 1 from it otherwise.

## Cost-Algebra for MOSP and Graph-Clear

We show that the cost expressions in the DP models for MOSP and graph-clear satisfy the property of cost-algebra. In these models, the cost expressions are in the form of $\max \left\{e_{\tau}(S), V(S \llbracket \tau \rrbracket)\right\}$ instead of $e_{\tau}(S)+V(S \llbracket \tau \rrbracket)$.

A cost-algebra (Edelkamp, Jabbar, and Lafuente 2005) is defined as a 6 -tuple $\langle A, \sqcup, \times, \preceq, \mathbf{0}, \mathbf{1}\rangle$ where $A$ is a set, $\times$ : $A \times A \rightarrow A$ is a binary operator, $\preceq \in A \times A$ is a binary relation, $\mathbf{0}, \mathbf{1} \in A$, and $\sqcup: 2^{A} \rightarrow A$ is an operator to select one element from a subset of $A$. It must satisfy the following conditions.

1. $\forall a, b \in A, a \times b \in A$
2. $\forall a, b, c \in A, a \times(b \times c)=(a \times b) \times c$
3. $\forall a \in A, a \times \mathbf{1}=\mathbf{1} \times a=a$
4. $\forall a \in A, a \preceq a$
5. $\forall a, b \in A, a \preceq b \wedge b \preceq a \Rightarrow a=b$
6. $\forall a, b, c \in A, a \preceq b \wedge b \preceq c \Rightarrow a \preceq c$
7. $\forall a, b \in A, a \preceq b \vee b \preceq a$
8. $\forall B \subseteq A, \forall b \in B, \sqcup B \preceq b$
9. $\forall a \in A, a \preceq \mathbf{0}$ and $\mathbf{1} \preceq a$
10. $\forall a, b, c \in A, a \preceq b \Rightarrow a \times c \preceq b \times c$ and $c \times a \preceq c \times b$

Conditions 1-3 ensure that $\langle A, \times, \mathbf{1}\rangle$ is a monoid. Conditions $4-7$ ensure that $\preceq$ is a total order. Condition 10 is called isotonicity.

Edelkamp, Jabbar, and Lafuente (2005) proved that $\left\langle\mathbb{R}^{+} \cup\right.$ $\{+\infty\}, \min ,+, \leq,+\infty, 0\rangle$, which corresponds to the shortest path problem, satisfies the conditions. We show that a tuple $\left\langle\mathbb{R}^{+} \cup\{+\infty\}\right.$, min, max $\left., \leq,+\infty, 0\right\rangle$ satisfies the conditions, which corresponds to the cost expresssions in the DP models for MOSP and graph-clear. The tuple $\left\langle\mathbb{R}^{+} \cup\{+\infty\}, \max , 0\right\rangle$ is a monoid since $\max \{a, b\} \in$ $\mathbb{R}, \max \{a, \max \{b, c\}\}=\max \{\max \{a, b\}, c\}$, and $\max \{a, 0\}=\max \{0, a\}=a$. Conditions 4-9 hold since $\left\langle\mathbb{R}^{+} \cup\{+\infty\}, \min ,+, \leq,+\infty, 0\right\rangle$ is a cost-algebra. For the isotonicity, $\max \{a, c\} \leq \max \{b, c\}$ and $\max \{c, a\} \leq$ $\max \{c, b\}$ for $a \leq b$.

## DyPDL Representations

We present DyPDL representations and YAML-DyPDL domain files of the DP models for CVRP in Table 1 and Listing 1, for SALBP-1 in Table 2 and Listing 2, for bin packing in Table 3 and Listing 3, for MOSP in Table 4 and Listing 4, and for graph-clear in Table 5 and Listing 5.

In SALBP-1, open-station is a forced transition in the YAML-DyPDL domain file. While it is not necessarily in theory because the other transitions are not applicable when open-station is applicable, it can be beneficial since a solver does not need to evaluate the preconditions of the other transitions.

| $\mathcal{V}$ | Type | Objects | Preference |
| :---: | :---: | :---: | :---: |
| $U$ | set | customer |  |
| $i$ | element | customer |  |
| $l$ | numeric |  | less |
| $k$ | numeric |  | less |
| $\mathcal{K}$ | Type | Indices |  |
| $q$ | numeric  <br> numeric  <br> numeric $j \in N$ <br> numeric $j, p \in N$ <br> numeric $j, p \in N$ |  |  |
| $m$ |  |  |  |
| $d_{j}$ |  |  |  |
| $c_{j p}$ |  |  |  |
| $c_{j p}^{\prime}$ |  |  |  |
| $S^{0}$ | $\begin{aligned} & \langle U=N \backslash\{0\}, i=0, l=0, k=1\rangle \\ & \{\{U=\emptyset, i=0\}\} \\ & \emptyset \\ & 0 \end{aligned}$ |  |  |
| $\mathcal{B}$ |  |  |  |
| $\mathcal{C}$ |  |  |  |
| $h$ |  |  |  |
| $\mathcal{T}$ | eff cost pre |  |  |
| visit $j$ | $\begin{array}{ll} U \leftarrow U \backslash\{j\} \quad c_{i j}+V(S \llbracket \tau \rrbracket) & j \in U \\ i \leftarrow j & l+d_{j} \leq q \\ l \leftarrow l+d_{j} & \\ \hline \end{array}$ |  |  |
| visit $j$ via the depot | $\begin{array}{ll} U \leftarrow U \backslash\{j\} \quad c_{i j}^{\prime}+V(S \llbracket \tau \rrbracket) & j \in U \\ i \leftarrow j & k<m \\ l \leftarrow d_{j} & \\ k \leftarrow k+1 & \end{array}$ |  |  |
| return | $i \leftarrow 0 \quad c_{i 0}+V(S \llbracket \tau \rrbracket) \begin{aligned} & U=\emptyset \\ & \\ & \\ & i \neq 0 \end{aligned}$ |  |  |

Table 1: DyPDL representation of the DP model for CVRP. No forced transition exists in this model.

| $\mathcal{V}$ | Type | Objects | Preference |
| :---: | :---: | :---: | :---: |
| $U$ |  | tasks $N$ |  |
| $r$ | numeric |  | more |
| $\mathcal{K}$ | Type | Objects | Indices |
| $c$ | numeric |  |  |
| $t_{i}$ | numeric |  | $i \in N$ |
| $P_{i}$ |  | tasks $N$ | $i \in N$ |
| $w_{i}^{2}$ | numeric |  | $i \in N$ |
| $w_{i}^{\prime 2}$ | numeric |  | $i \in N$ |
| $w_{i}^{3}$ | numeric |  | $i \in N$ |
| $S^{0}$ | $\begin{aligned} & \langle U=N, r=0\rangle \\ & \{\{U=\emptyset\}\} \\ & \emptyset \end{aligned}$ |  |  |
| $\mathcal{B}$ |  |  |  |
| $\mathcal{C}$ |  |  |  |
| $h$ | $\max \left\{\begin{array}{l} \left\lceil\left(\sum_{i \in U} t_{i}-r\right) / c\right\rceil \\ \sum_{u \in U} w_{i}^{2}+\left\lceil\sum_{i \in U} w_{i}^{\prime 2}\right\rceil-l^{2} \\ \left\lceil\sum_{i \in U} w_{i}^{3}\right\rceil-l^{3} \end{array}\right.$ |  |  |
| $\mathcal{T}$ | eff | cost | pre |
| assign $i$ | $\begin{aligned} & U \leftarrow U \backslash\{i\} \\ & r \leftarrow r-t_{i} \end{aligned}$ | $V(S \llbracket \tau \rrbracket)$ | $\begin{aligned} & i \in U \\ & P_{i} \cap U=\emptyset \\ & r \geq t_{i} \end{aligned}$ |
| open a station | $r \leftarrow c$ | $1+V(S$ | $U^{\prime}=\emptyset$ |

Table 2: DyPDL representation of the DP model for SALBP1 , where $U^{\prime}=\left\{i \in U \mid P_{i} \cap U=\emptyset \wedge r \geq t_{i}\right\}, l^{2}=1$ if $r \geq c / 2$ and $l^{2}=0$ otherwise, and $l^{3}=1$ if $r \geq c / 3$ and $l^{3}=0$ otherwise.

| $\mathcal{V}$ | Type | Objects | Preference |  |
| :---: | :---: | :---: | :---: | :---: |
| U | set | items $N$ |  |  |
| $r$ | numeric |  | more |  |
| $k$ | element | items $N$ | less |  |
| $\mathcal{K}$ | Type | Indices |  |  |
| c | numeric |  |  |  |
| $t_{i}$ | numeric | $i \in N$ |  |  |
| $w_{i}^{2}$ | numeric | $i \in N$ |  |  |
| $w_{i}^{\prime 2}$ | numeric | $i \in N$ |  |  |
| $w_{i}^{3}$ | numeric | $i \in N$ |  |  |
| $S^{0}$ | $\langle U=N, r=$ | , $k=0\rangle$ |  |  |
| $\mathcal{B}$ | $\{\{U=\emptyset\}\}$ |  |  |  |
| $\mathcal{C}$ | $\emptyset$ |  |  |  |
| $h$ | $\max \left\{\begin{array}{l} \left\lceil\left(\sum_{i}\right.\right. \\ \sum_{u \in} \\ \Gamma \sum_{i \epsilon} \end{array}\right.$ | $\begin{gathered} \left.\left.\in U t_{i}-r\right) / c\right\rceil \\ w_{i}^{2}+\left\lceil\sum_{i \in U}\right. \\ \left.U_{i}^{3}\right\rceil-l^{3} \end{gathered}$ | $\left.w_{i}^{\prime 2}\right\rceil-l^{2}$ |  |
| $\underline{\mathcal{T}}$ | eff | cost | pre | forced |
| pack $i$ | $\begin{aligned} & U \leftarrow U \backslash\{i\} \\ & r \leftarrow r-t_{i} \end{aligned}$ | $V(S \llbracket \tau \rrbracket)$ | $\begin{aligned} & i \in U \\ & r \geq t_{i} \end{aligned}$ | $\perp$ |
| open with $i$ | $\begin{aligned} & U \leftarrow U \backslash\{i\} \\ & r \leftarrow c-t_{i} \\ & k \leftarrow k+1 \end{aligned}$ | $1+V(S \llbracket \tau \rrbracket)$ | $\begin{aligned} & U^{1}=\bar{\emptyset} \\ & i \in U \\ & i \geq k \end{aligned}$ |  |

Table 3: DyPDL representation of the DP model for bin packing, where $U^{1}=\left\{i \in U \mid r \geq t_{i} \wedge i+1 \geq k\right\}$, $l^{2}=1$ if $r \geq c / 2$ and $l^{2}=0$ otherwise, and $l^{3}=1$ if $r \geq c / 3$ and $l^{3}=0$ otherwise.

| $\mathcal{V}$ | Type | Objects |  |
| :--- | :--- | :--- | :--- |
| $R$ | set | customers $C$ |  |
| $O$ | set | customers $C$ |  |
| $\mathcal{K}$ | Type | Objects | $c \in C$ |
| $N_{c}$ | set | customers $C$ |  |
| $S^{0}$ | $\langle R=C, O=\emptyset\rangle$ |  |  |
| $\mathcal{B}$ | $\{\{R=\emptyset\}\}$ |  |  |
| $\mathcal{C}$ | $\emptyset$ |  | pre |
| $h$ | 0 | cost | $c \in R$ |
| $\overline{\mathcal{T}}$ | eff |  |  |
|  | $R \leftarrow R \backslash\{c\}$ | $\max \begin{cases}V(S \llbracket \tau) & \\ \text { close } c & R \leftarrow O \cap R) \cup\left(N_{c} \backslash O\right) \\ & O \leftarrow O \cup N_{c}\end{cases}$ |  |

Table 4: DyPDL representation of the DP model for MOSP. No forced transition exists in this model.


```
Listing 2: YAML-DyPDL domain file for SALBP-1.
    objects:
    - task
    state_variables:
    - name: U
        type: set
        object: task
    - name: r
        type: integer
        preference: greater
    tables:
    - { name: c, type: integer }
    - name: t
        type: integer
        args: [task]
    - name: P
        type: set
        object: task
        args: [task]
        - name: w2_1
        type: integer
        args: [task]
    - name: w2_2
        type: continuous
        args: [task]
    - name: w3
        type: continuous
        args: [task]
    base_cases:
        - - (is_empty U)
    reduce: min
    cost_type: integer
    transitions:
    - name: assign
        parameters: [{ name: i, object: U }]
        preconditions:
            - (is_empty
                    (intersection U (P i)))
            - (<= (t i) r)
        effect:
            U: (remove i U)
            r: (- r (t i))
        cost: cost
    - name: open-station
        forced: true
        preconditions:
            - forall: [{ name: i, object: U }]
                condition: >
                    (or
                            (> (t i) r)
                            (> |(intersection U (P i))|
                                0))
        effect:
                r: C
            cost: (+ cost 1)
    dual_bounds:
        - (ceil (/ (- (sum t U) r) c))
        - (- (+ (sum w2_1 U)
            (ceil (sum w2_2 U)))
            (if (>= r (/ c 2.0)) 1 0))
    - (- (ceil (sum w3 U))
            (if (>= r (/ c 3.0)) 1 0))
```

Listing 3: YAML-DyPDL domain file for bin packing.
objects:
$-\quad$ item
state_variables:
- name: U
type: set
object: item
- name: r
type: integer
preference: greater
- name: k
type: element
object: item
preference: less
tables:
- name: c
type: integer
- name: t
type: integer
args: [item]
- name: w2_1
type: integer
args: [item]
- name: w2_2
type: continuous
args: [item]
- name: w3
type: continuous
args: [item]
base_cases:
- - (is_empty U)
reduce: min
cost_type: integer
transitions:
- name: pack
parameters: [\{name: i, object: U\}]
preconditions:
- $\left(<=\left(\begin{array}{l}\text { i }\end{array}\right)\right.$
$-\quad(>=(+i 1) \mathrm{k})$
effect:
U: (remove i U)
$r:(-r(t i))$
cost: cost
- name: open-with
forced: true
parameters: [\{name: i, object: U\}]
preconditions:
- (>= i k)
- forall: [\{name: j, object: U\}]
condition: (> ( $\quad$ j) $r$ )
effect:
U: (remove i U)
r: (-c (t i))
k: (+ 1 k)
cost: (+ cost 1)
dual_bounds:
- (ceil (/ (- (sum t U) r) c))
- (- (+ (sum w2_1 U)
(ceil (sum w2_2 U))
(if (>=r (/ c 2.0)) 1 0))
- (- (ceil (sum w3 U))
(if $(>=r(/ C 3.0)) 10$ )

|  | Listing 5: YAML-DyPDL domain file for graph-clear. |  |
| :---: | :---: | :---: |
|  | 1 | objects: <br> - node |
| Listing 4: YAML-DyPDL domain file for MOSP. | 3 | state_variables: |
| 1 objects: | 4 | - name: C |
| 2 - customer | 5 | type: set |
| 3 state_variables: | 7 | tables: |
| 4 - name: R | 8 | - name: "N" |
| 5 type: set | 9 |  |
| 6 object: customer | 10 | type: set |
| 7 - name: 0 | 11 | - object: node |
| 8 type: set | 12 | type: integer |
| 9 object: customer | 13 | type: integer |
| 10 tables: 11 "N" | 14 | args: node |
| 11 - name: "N" | 15 | _ name: b |
| 12 type: set | 16 | - name: b |
| 13 object: customer | 16 | type: integer |
| 14 args: | 17 | args: |
| 15 - customer | 19 | - node |
| 16 base_cases: | 19 | - node |
| 17 - - (is_empty R) | 20 | default: 0 |
| 18 reduce: min | 21 | base_cases: |
| 19 cost_type: integer | 22 |  |
| 20 transitions: | 24 | reduce: min |
| 21 - name: close | 25 | cost_type: integer |
| 22 parameters: | 26 | - name: sweep |
| 23 - name: c | 27 | - name: sweep |
| 24 object: R | 28 | parameters: |
| 25 effect: | 28 | - name: C |
| 26 R: (remove c R) | 29 | object: node |
| 27 O: (union 0 ( N c) ) | 30 | preconditions: |
| 28 cost: > | 31 | - (not (is_in c C)) |
| 29 (max cost | 32 | effect: |
| 30 I (union (intersection 0 R) | 33 | C: (add C C) |
| 31 (difference ( N c) O)) 1 ) | 34 35 | cost: > |
| 32 dual_bounds: |  | (max cost |
| $33-0$ | 37 | (+ (a c) |
|  | 38 | (sum b C (remove c ${ }^{\text {c }}$ C) )) )) |
|  | 39 | dual_bounds: |
|  | 40 | - 0 |

## Experimental Results

In addition to the number of instances solved to optimality, we also evaluate the computational time to find an optimal solution. We take the average time over instances solved by all methods. Furthermore, we evaluate the best lower bound found by the algorithm. In CAASDy, the minimum $f$-value of states in the open list is a lower bound on the optimal solution. For each instance, we compute the ratio of the lower bound found by a method to the best lower bound found by all the methods. Concretely, if there are methods $1 \ldots, n$, and method $i$ finds a lower bound $L_{i}$, then, the lower bound ratio is defined as $\frac{L_{i}}{\max _{j=1, \ldots, n} L_{j}}$. Thus, higher is better and 1.0 is the maximum.

For TSPTW, we also evaluate the decision diagram-based solver, ddo (Gillard, Schaus, and Coppé 2020) since it was previously used in TSPTW. We use the 'barrier' solver of ddo ${ }^{1}$ (Coppé, Gillard, and Schaus 2022). Since the original version is used to solve problems to minimize the makespan objective, we modified the code so that it minimizes the total travel time.

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[^1]|  | MIP |  |  | CP |  |  | Ddo |  |  | DP |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| TSPTW | \# | time | LB | \# | time | LB | \# | time | LB | \# | time | LB |
| Dumas (135) | 121 | 0.39 | 0.97 | 36 | 52.61 | 0.43 | 114 | 0.11 | 0.86 | 135 | 0.04 | 1.00 |
| GDE (130) | 71 | 1.38 | 0.71 | 4 | 289.20 | 0.16 | 35 | 1.53 | 0.73 | 77 | 0.07 | 0.71 |
| OT (25) | 0 | - | 0.00 | 0 | - | 0.66 | 0 | - | 0.32 | 0 | - | 0.67 |
| AFG (50) | 33 | 546.92 | 0.80 | 7 | 16.02 | 0.40 | 30 | 0.30 | 0.81 | 45 | 0.04 | 0.95 |
| Total (340) | 225 | 61.20 | 0.77 | 47 | 69.58 | 0.34 | 179 | 0.26 | 0.77 | 257 | 0.04 | 0.86 |
| CVRP | \# | time | LB | \# | time | LB | \# | time | LB | \# | time | LB |
| A, B, E, F, P (90) | 26 | - | 0.94 | 0 | - | 0.05 |  | - | - | 4 | - | 0.22 |
| SALBP-1 | \# | time | LB | \# | time | LB | \# | time | LB | \# | time | LB |
| Small (525) | 525 | 0.25 | 1.00 | 525 | 0.19 | 1.00 |  |  |  | 525 | 0.04 | 1.00 |
| Medium (525) | 518 | 35.28 | 1.00 | 501 | 15.30 | 1.00 |  |  | - | 509 | 2.38 | 0.99 |
| Large (525) | 317 | 103.44 | 0.75 | 404 | 3.37 | 0.99 | - | - | - | 414 | 1.20 | 0.88 |
| Very large (525) | 0 | - | 0.00 | 155 | - | 0.97 | - | - | - | 204 | - | 0.54 |
| Total (2100) | 1360 | 37.31 | 0.69 | 1585 | 6.47 | 0.99 | - | - | - | 1652 | 1.17 | 0.85 |
| Bin Packing | \# | time | LB | \# | time | LB | \# | time | LB | \# | time | LB |
| Falkenauer U (80) | 25 | 64.49 | 0.94 | 36 | 2.29 | 1.00 |  | - | - | 33 | 1.61 | 0.47 |
| Falkenauer T (80) | 37 | 147.01 | 1.00 | 56 | 8.16 | 1.00 | - | - | - | 27 | 7.19 | 0.40 |
| Scholl 1 (720) | 605 | 16.88 | 0.95 | 533 | 19.13 | 1.00 | - | - | - | 517 | 15.70 | 0.85 |
| Scholl 2 (480) | 354 | 34.11 | 0.97 | 445 | 0.37 | 1.00 | - | - | - | 335 | 3.12 | 0.73 |
| Scholl 3 (10) | 0 | - | 1.00 | 1 | - | 1.00 | - | - | - | 0 | - | 0.09 |
| Falkenauer U | 25 | 64.49 | 0.94 | 36 | 2.29 | 1.00 | - | - | - | 33 | 1.61 | 0.47 |
| Wäscher (17) | 2 | 788.96 | 1.00 | 10 | 3.22 | 1.00 | - | - | - | 10 | 1.29 | 0.62 |
| Schwerin 1 (100) | 80 | - | 1.00 | 96 | - | 1.00 | - | - | - | 0 | - | 0.06 |
| Schwerin 2 (100) | 54 | - | 1.00 | 61 | - | 1.00 | - | - | - | 0 | - | 0.09 |
| Hard 28 (28) | 0 | - | 1.00 | 0 | - | 1.00 | - | - | - | 0 | - | 0.32 |
| Total (1615) | 1157 | 30.89 | 0.97 | 1238 | 11.09 | 1.00 | - | - | - | 922 | 10.19 | 0.66 |
| MOSP | \# | time | LB | \# | time | LB | \# | time | LB | \# | time | LB |
| Constraint Modelling Challenge (46) | 41 | 10.32 | 0.94 | 44 | 4.53 | 0.96 | - | - | - | 44 | 0.06 | 1.00 |
| SCOOP Project (24) | 8 | 144.30 | 0.64 | 23 | 0.50 | 0.99 | - | - | - | 16 | 0.04 | 0.95 |
| Faggioli and Bentivoglio (300) | 130 | 88.66 | 0.75 | 300 | 1.77 | 1.00 | - | - | - | 298 | 0.04 | 1.00 |
| Chu and Stuckey (200) | 44 | 98.50 | 0.47 | 70 | 58.10 | 0.49 | - | - | - | 125 | 0.07 | 1.00 |
| Total (570) | 223 | 76.94 | 0.66 | 437 | 10.57 | 0.82 | - | - | - | 483 | 0.05 | 1.00 |
| Graph-Clear | \# | time | LB | \# | time | LB | \# | time | LB | \# | time | LB |
| Planar (60) | 16 | 447.49 | 0.98 | I | 297.12 | 0.82 | - | - | - | 20 | 0.18 | 1.00 |
| Random (75) | 8 | 65.35 | 0.85 | 3 | 9.44 | 0.52 | - | - | - | 25 | 0.41 | 1.00 |
| Total (135) | 24 | 160.89 | 0.91 | 4 | 81.36 | 0.65 | - | - | - | 45 | 0.36 | 1.00 |
| Average ratio | 0.48 |  |  | 0.41 |  |  | - |  |  | 0.59 |  |  |

Table 6: Number of instances solved to optimality ('\#'), the time to solve averaged over instances solved by all the methods ('time'), and the average lower bound ratio to the best lower bound found by all the methods ('LB'). 'Average ratio' is the ratio of optimally solved instances in each problem class averaged over all problem classes.


[^0]:    *This document is an appendix for a paper published at the 33rd International Conference on Automated Planning and Scheduling (ICAPS 2023) (Kuroiwa and Beck 2023)

[^1]:    ${ }^{1}$ https://github.com/vcoppe/ddo-barrier

