## Advances in Model-Based Optimization with AMPL

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## Formulating Models More Like You Think About Them

Describe an optimization problem

- In a form you find natural or convenient
- Using readily recognized expressions

Send it to a solver

- In a form the solver will accept
- Relying on the modeling software to translate

Get back a result

- In the form you originally used


## Typical User Complaint

```
Thank you so much for replying.
Let me show my "if-then" constraint in a more clear way as follows:
set veh := {1..16 by 1};
param veh_ind {veh};
param theory_time {veh};
param UP := 400000;
var in_lane_veh {veh} integer >=1, <=2;
var in_in_time {veh} >=0, <=UP;
Note that "in_lane_veh {veh}" are integer variables which equal 1 or 2,
and "in_in_time {veh}" are continuous variables.
subject to IfConstr {i in 1..card(veh)-1, j in i+1..card(veh):
    veh_ind[i] = veh_ind[j] and theory_time[i] <= theory_time[j]}:
        in_lane_veh[i] = in_lane_veh[j] ==> in_in_time[j] >= in_in_time[i] + l_veh/v;
```

When I run my program, there appears the following statement:
CPLEX 20.1.0.0: logical constraint _slogcon[1] is not an indicator constraint.

## Typical Reply

— — -
To reformulate this model in a way that your MIP solver would accept, you could define some more binary variables,
var in_lane_same \{veh, veh\} binary;
with the idea that in_lane_same[i,j] should be 1 if and only if in_lane_veh[i] = in_lane_veh[j]. Then the desired relation could be written as two constraints:
in_lane_veh[i] = in_lane_veh[j] ==> in_lane_same[i,j] =1

The second one is an indicator constraint, but you would just need to replace the first one by equivalent linear constraints.

Given that in_lan_veh can only be either 1 or 2 , those constraints could be
in_lane_same $[i, j]>=3-i n \_$lane_veh[i] - in_lane_veh[j]
in_lane_same[i,j] >= in_lane_veh[i] + in_lane_veh[j]-3

## New Solver Interface Library (MP)

Design

- C++ library for building efficient, configurable solver drivers
- Support for features of current C interface library
- Extensive toolset for problem recognition and transformation


## Motivation . . .

- AMPL has logical and "not linear" expressions for writing models the way you think of them
- Old interfaces have very limited support for these
- New interfaces, built with MP, allow these expressions to be used and combined freely


## Example: Multi-Product Network Flow

-     -         - 

Motivation

- Ship products efficiently to meet demands

Context

- a transportation network
- Nodes Orepresenting cities
- arcs $\longrightarrow$ representing roads
- supplies $-\rightarrow$ at nodes
- demands $-\rightarrow$ at nodes
- capacities on arcs
- shipping costs on arcs



## Example: Multi-Product Network Flow

Decide

- how much of each product to ship on each arc

So that

- shipping costs are kept low
- shipments on each arc respect capacity of the arc
- supplies, demands, and shipments are in balance at each node



## AMPL Model for Multi-Product Network Flow

```
set PRODUCTS;
set NODES;
param net_inflow {PRODUCTS,NODES};
set ARCS within {NODES,NODES};
param capacity {ARCS} >= 0;
param var_cost {PRODUCTS,ARCS} >= 0;
var Flow {PRODUCTS,ARCS} >= 0;
minimize TotalCost:
    sum {p in PRODUCTS, (i,j) in ARCS} var_cost[p,i,j] * Flow[p,i,j];
subject to Capacity {(i,j) in ARCS}:
    sum {p in PRODUCTS} Flow[p,i,j] <= capacity[i,j];
subject to Conservation {p in PRODUCTS, j in NODES}:
        sum {(i,j) in ARCS} Flow[p,i,j] + net_inflow[p,j] =
        sum {(j, i) in ARCS} Flow[p,j, i];
```


## Example with conditions: Multi-Product Network Flow

## Decide also

- whether to use each arc


## So that

- variable costs plus fixed costs for shipping are kept low
- shipments are not too small
- not too many arcs are used



## Positive Shipments Incur Fixed Costs

-     -         - 

Linearization

```
param fix_cost {ARCS} >= 0;
var Use {ARCS} binary;
minimize TotalCost:
    sum {p in PRODUCTS, (i,j) in ARCS} var_cost[p,i,j] * Flow[p,i,j] +
    sum {(i,j) in ARCS} fix_cost[i,j] * Use[i,j];
```

How you think about it

```
param fix_cost {ARCS} >= 0;
minimize TotalCost:
    sum {p in PRODUCTS, (i,j) in ARCS} var_cost[p,i,j] * Flow[p,i,j] +
    sum {(i,j) in ARCS}
        if exists {p in PRODUCTS} Flow[p,i,j] > 0 then fix_cost[i,j];
```


## Shipments Can’t Be Too Small

Linearization

```
subject to Min_Shipment {(i,j) in ARCS}:
    sum {p in PRODUCTS} Flow[p,i,j] >= min_ship * Use[i,j];
subject to Capacity {(i,j) in ARCS}:
    sum {p in PRODUCTS} Flow[p,i,j] <= capacity[i,j] * Use[i,j];
```

How you think about it

```
subject to Shipment_Limits {(i,j) in ARCS}:
    sum {p in PRODUCTS} Flow[p,i,j] = 0 or
    min_ship <= sum {p in PRODUCTS} Flow[p,i,j] <= capacity[i,j];
```


## Can't Use Too Many Arcs

-     -         - 

Linearization

```
subject to Max_Used:
    sum {(i,j) in ARCS} Use[i,j] <= max_arcs;
```

How you think about it

```
subject to Limit_Used:
    atmost max_arcs {(i,j) in ARCS}
        (sum {p in PRODUCTS} Flow[p,i,j] > 0);
```


## Linearization is Usually Not That Easy!

```
subject to IfConstr {i in 1..card(veh)-1, j in i+1..card(veh):
    veh_ind[i] = veh_ind[j] and theory_time[i] <= theory_time[j]}:
    in_lane_veh[i] = in_lane_veh[j]
        ==> in_in_time[j] >= in_in_time[i] + l_veh/V;
```

minimize total_fuelcost:
$\operatorname{sum}\{(i, j)$ in $A\} \operatorname{sum}\{k$ in $V\} \quad X[i, j, k]$ *
( (if $H[i, k]<=300$ then $\operatorname{dMor}[i, j]$ else
if $\mathrm{H}[\mathrm{i}, \mathrm{k}]$ <= 660 then $\operatorname{dAft}[\mathrm{i}, \mathrm{j}]$ else
if $\mathrm{H}[\mathrm{i}, \mathrm{k}]<=901$ then dEve $[i, j])$ * $5+$
(if $\mathrm{H}[\mathrm{i}, \mathrm{k}]$ <= 300 then $\operatorname{tMor}[\mathrm{i}, \mathrm{j}]$ else
if $\mathrm{H}[\mathrm{i}, \mathrm{k}]$ <= 660 then $\operatorname{tAft}[\mathrm{i}, \mathrm{j}]$ else
if $H[i, k]<=901$ then tEve[i,j]) * 0.0504);

```
subject to NoPersonIsolated
        {l in TYPES['loc'], r in TYPES['rank'], j in 1..numberGrps}:
    sum {i in LOCRANK[l,r]} Assign[i,j] = 0 or
    sum {i in LOCRANK[l,r]} Assign[i,j] + sum {a in ADJACENT[r]} sum {i in LOCRANK[l,a]} Assign[i,j] >= 2;
```


## Example: N-Queens

## How can $n$ queens be placed on an $n \times n$ chessboard so that no two of them attack each other?

Constraint alldiff enforces a set of integer variables to take distinct values. Using alldiff, we can model $N$-Queens as follows:

```
param n integer > 0; # N-queens
var Row {1..n} integer >= 1 <= n;
s.t. row_attacks: alldiff ({j in l..n} Row[j]);
s.t. diag_attacks: alldiff ({j in 1..n} Row[j]+j);
s.t. rdiag_attacks: alldiff ({j in 1..n} Row[j]-j);
```



## Example: N-Queens (https://colab.ampl.com)



12s \# Google Colab \& Kaggle integration from amplpy import AMPL, tools ampl = tools.ampl_notebook(
modules=["highs"], \# modules to install
license_uuid="default") \# license to use
(>
license_uuid="defaul
license_uuid="default") \# license to use

曰
Using default Community Edition License for Colab. Get yours at: https://ampl.com/ce Licensed to AMPL Community Edition License for the AMPL Model Colaboratory (https://colab.ampl.com).

## Example：N－Queens（https：／／colab．ampl．com）


－Solving with HiGHS and displaying the solution
ampl．param［＂n＂］＝n
ampl．option［＂solver＂］＝＂highs＂
ampl．option［＂highs＿options＂］＝＂outlev＝0＂ ampl．option［
2. solution $=$ ampl．get＿data（＂Row＂）．to＿dict（）

## Example: N-Queens (https://colab.ampl.com)



## Example: N-Queens (https://colab.ampl.com)



## Example: Recharging strategy for an electric vehicle (https://mo-book.ampl.com/)



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minimize min_time: t_arr[n + 1];
s.t. drive_time \{i in SEGMENTS\}: t_arr[i] == t_dep[i-1] + dist[i]/v;
s.t. rest_time \{i in SEGMENTS\}: r_arr[i] == r_dep[i-1] + dist[i]/v;
s.t. drive_distance $\{\mathrm{i}$ in SEGMENTS\}: $\mathrm{x}[\mathrm{i}]==\mathrm{x}[\mathrm{i}-1]+$ dist[i];
s.t. discharge \{i in SEGMENTS\}: c_arr[i] == c_dep[i-1] - R * dist[i];
s.t. recharge \{i in STATIONS\}:
\# list of constraints that apply if there is no stop at station i
((c_dep[i] == c_arr[i] and t_dep[i] == t_arr[i] and r_dep[i] == r_arr[i])
or
\# list of constraints that apply if there is a stop at station i
(t_dep[i] == t_lost + t_arr[i] + (c_dep[i] - c_arr[i])/C[i] and c_dep[i] >= c_arr[i] and r_dep[i] == 0))
and not
((c_dep[i] == c_arr[i] and t_dep[i] == t_arr[i] and r_dep[i] == r_arr[i]) and
(t_dep[i] == t_lost + t_arr[i] + (c_dep[i] - c_arr[i])/C[i] and
c_dep[i] >= c_arr[i] and r_dep[ī] == 0));

## Supported Extensions

Operators and functions

- Conditional: if-then-else; ==>, <==, <==>
- Logical: or, and, not; exists, forall
- Piecewise linear: abs; min, max; <<breakpoints; slopes>>
- Counting: count; atmost, atleast, exactly; numberof
- Comparison: >, <, !=; alldiff
- Complementarity: complements
- Nonlinear: *, /, ^; exp, log; sin, cos, tan; sinh, cosh, tanh
- Set membership: in

Expressions and constraints

- High-order polynomials
- Second-order cones
- exponential cones (MOSEK driver!)


## Supported Solvers

Solvers

- Gurobi, Xpress, COPT, MOSEK
- HigHS, CBC, SCIP, GCG
- CPLEX soon

Modeling guide

- https://mp.ampl.com/model-quide.html

Examples using MP features

- https://colab.ampl.com
- https://mo-book.ampl.com (NEW BOOK!)


## Small promo: Our main talk is right after this session!

Technology Tutorial, Tuesday, October 17, 2:55-3:30 pm Location: CC-North 120 D

Python and AMPL: Build Prescriptive Analytics applications quickly with Pandas, Colab, Streamlit, and amplpy

