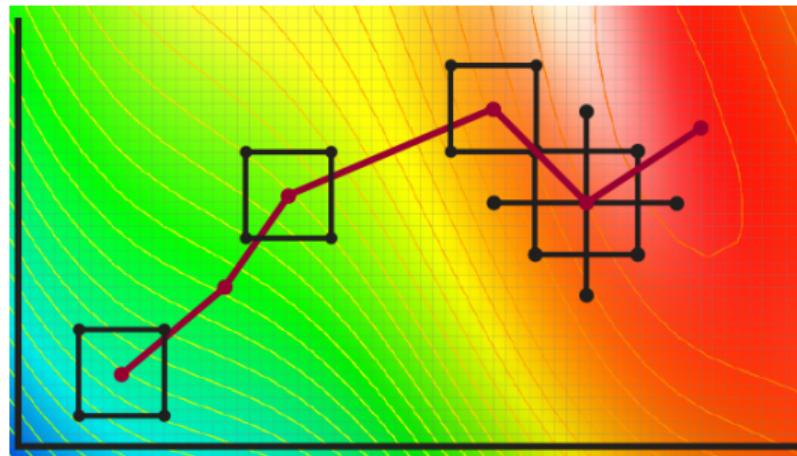


Experimentation for Improvement



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Design and Analysis of Experiments

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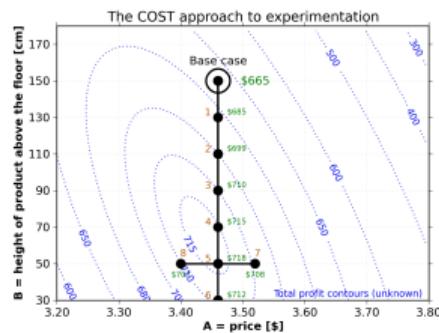
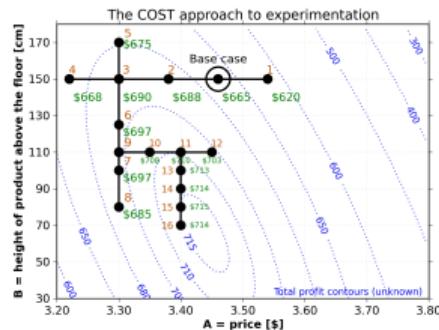
- ▶ **to share** - to copy, distribute and transmit the work, including print it
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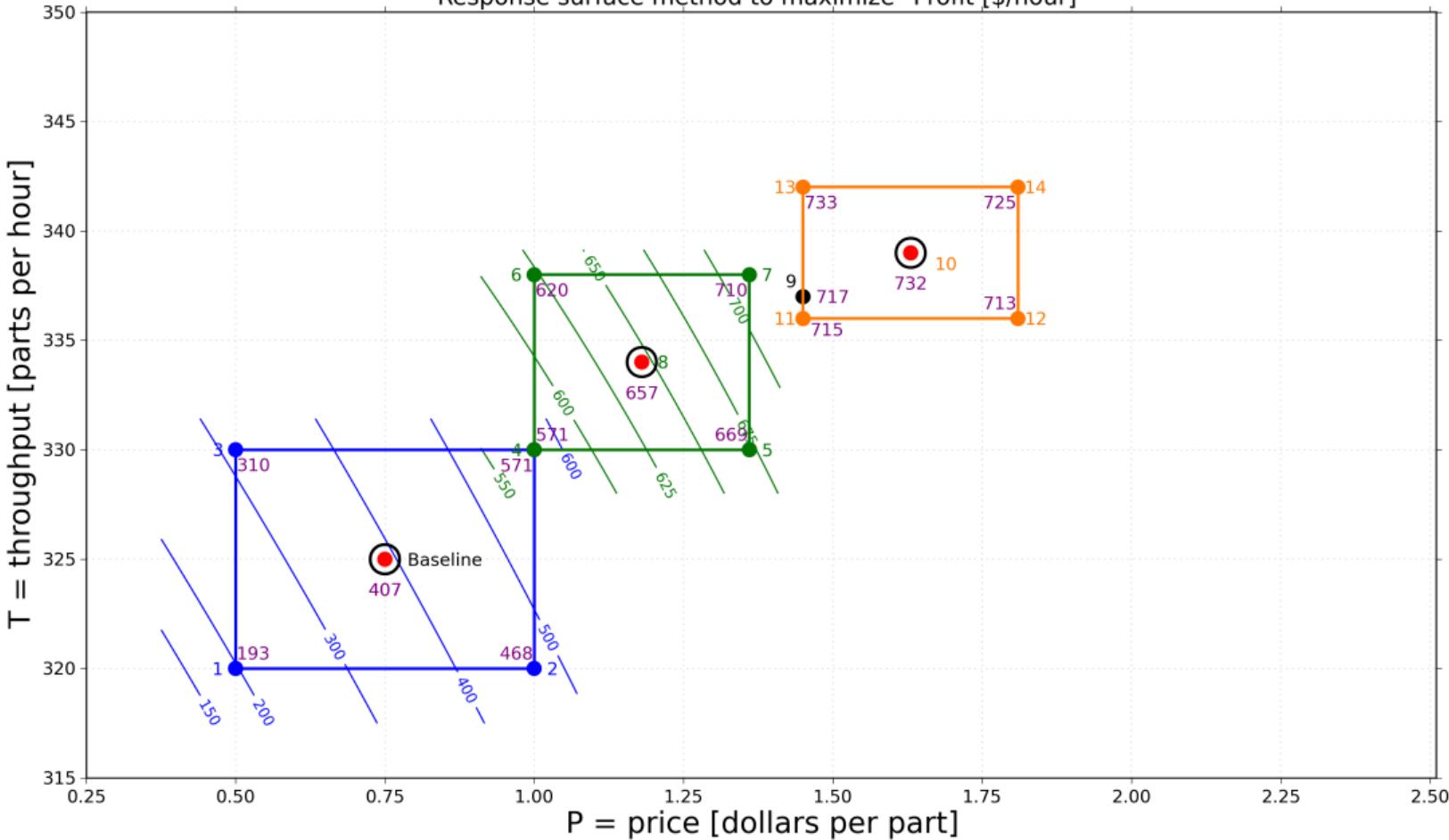
Before we get started: a quick look back at OFAT (COST)

OFAT is not recommended for a variety of reasons:

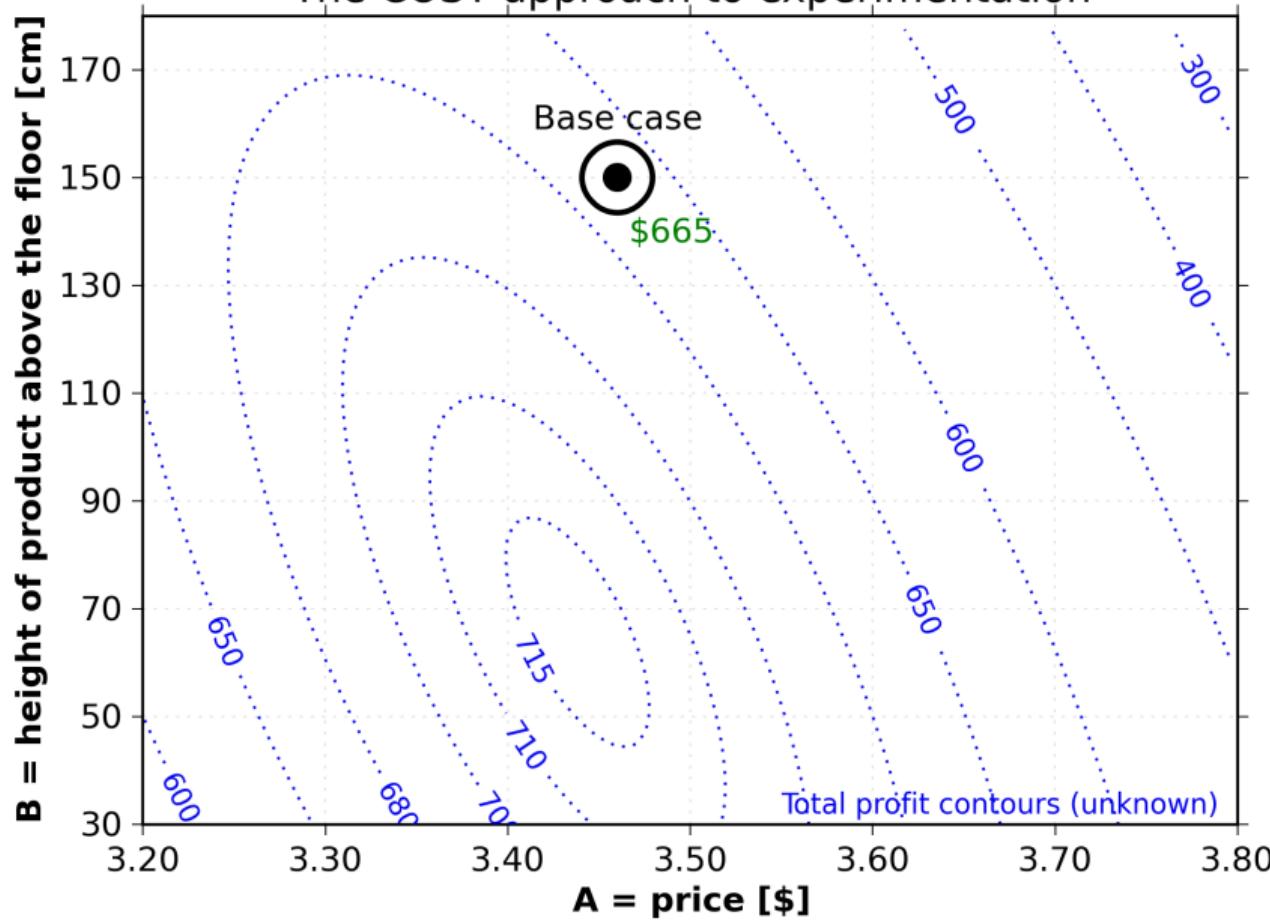
- ▶ With OFAT you are never really sure you are at the peak.
 - ▶ you keep iterating through all the factors
 - ▶ no conclusive indication that you converged
 - ▶ OFAT is order-dependent (it is a lottery!)
 - ▶ OFAT does not scale well
 - ▶ For 3 or more factors: we often end up using more runs
 - ▶ For 2 factors: I find OFAT and RSM (response surface methods) use about the same number of runs
 - ▶ We don't learn about interactions; only about main effects



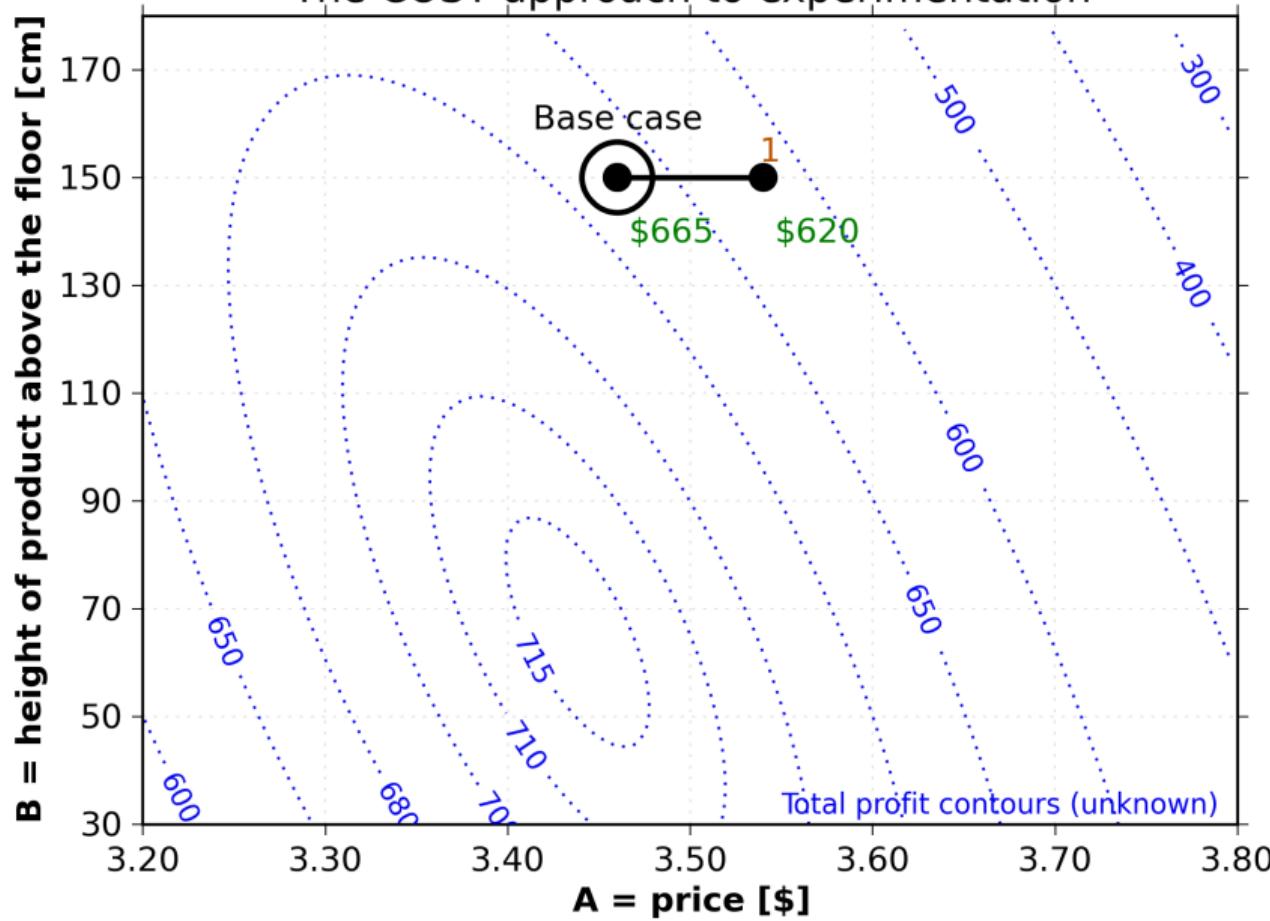
Response surface method to maximize "Profit [\$/hour]"



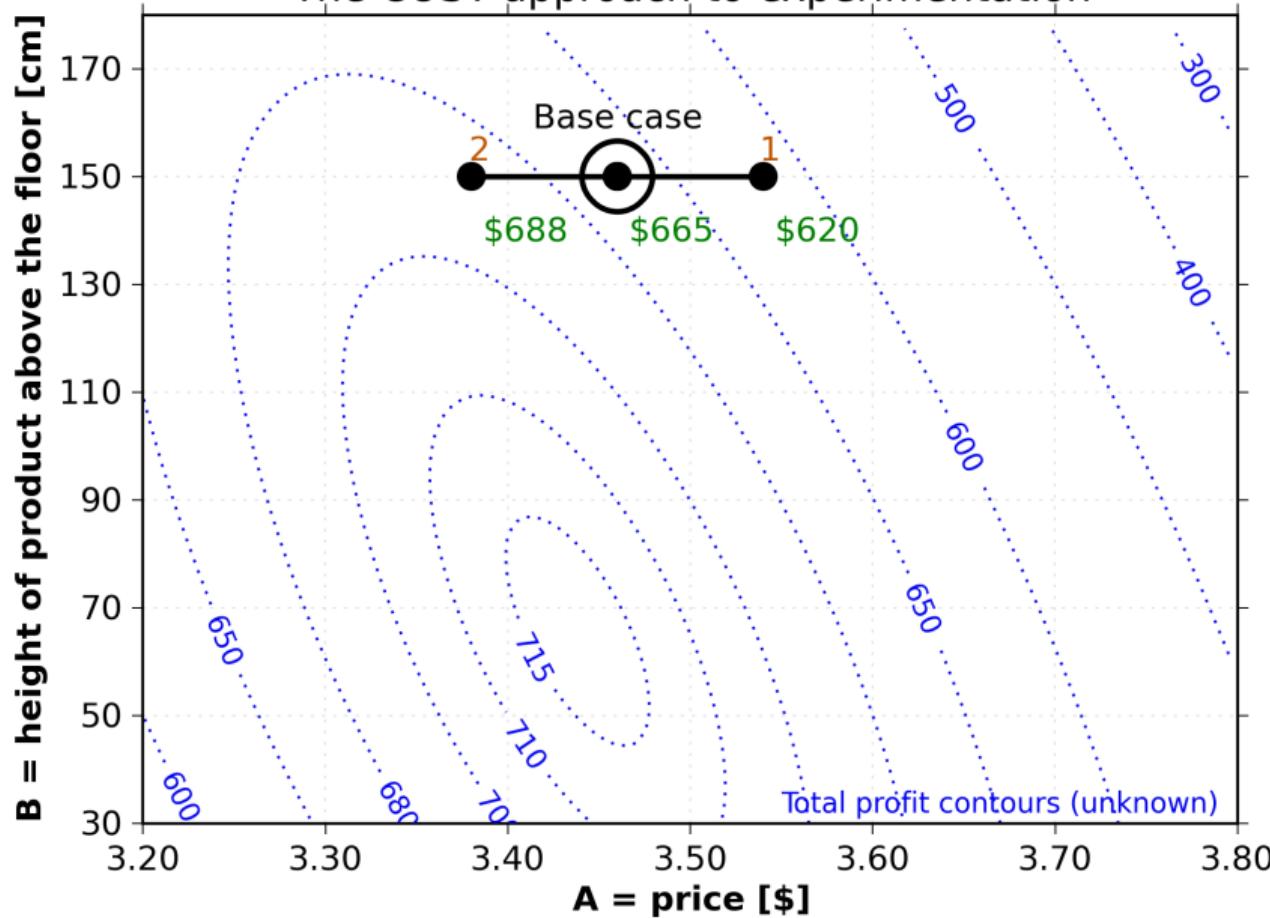
The COST approach to experimentation



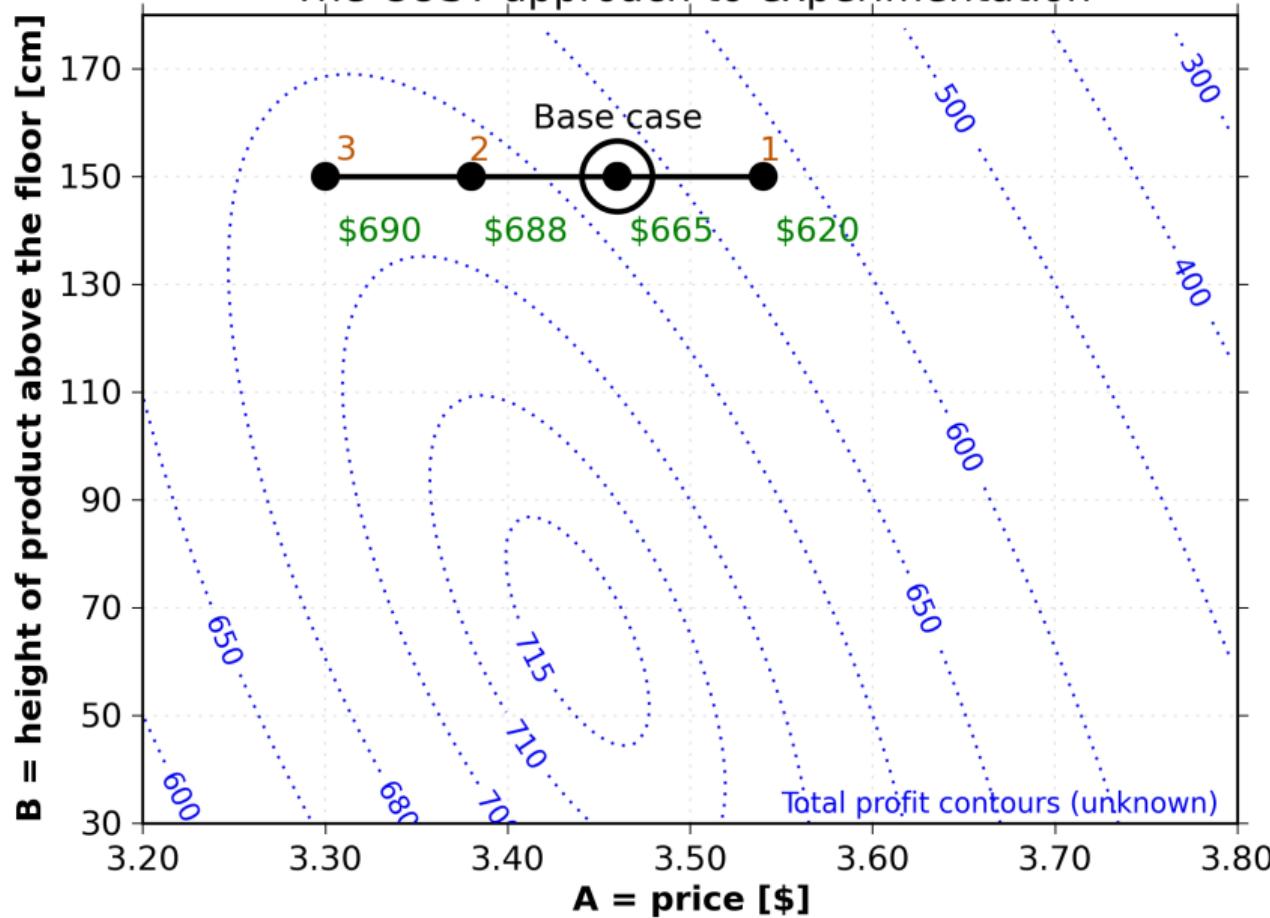
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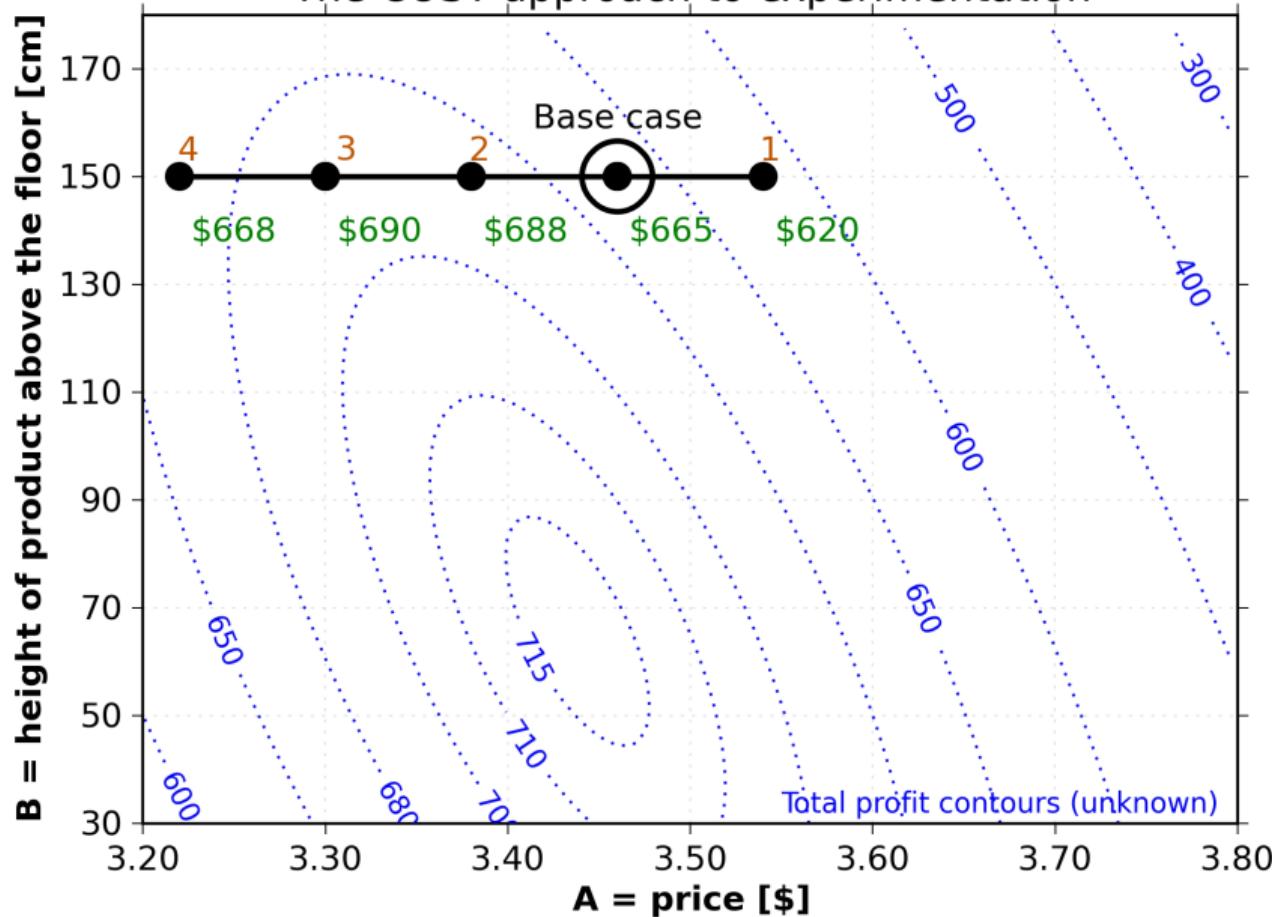
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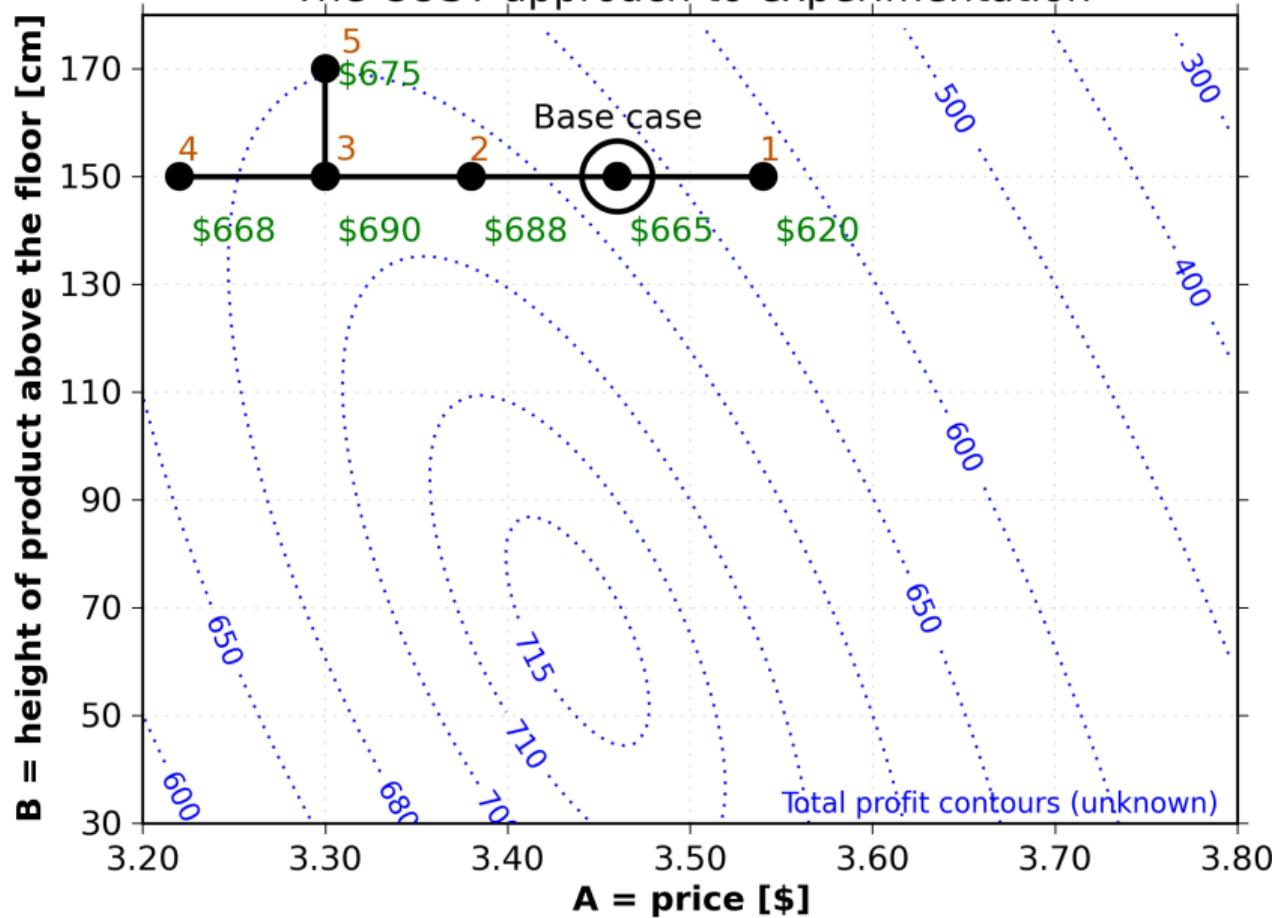
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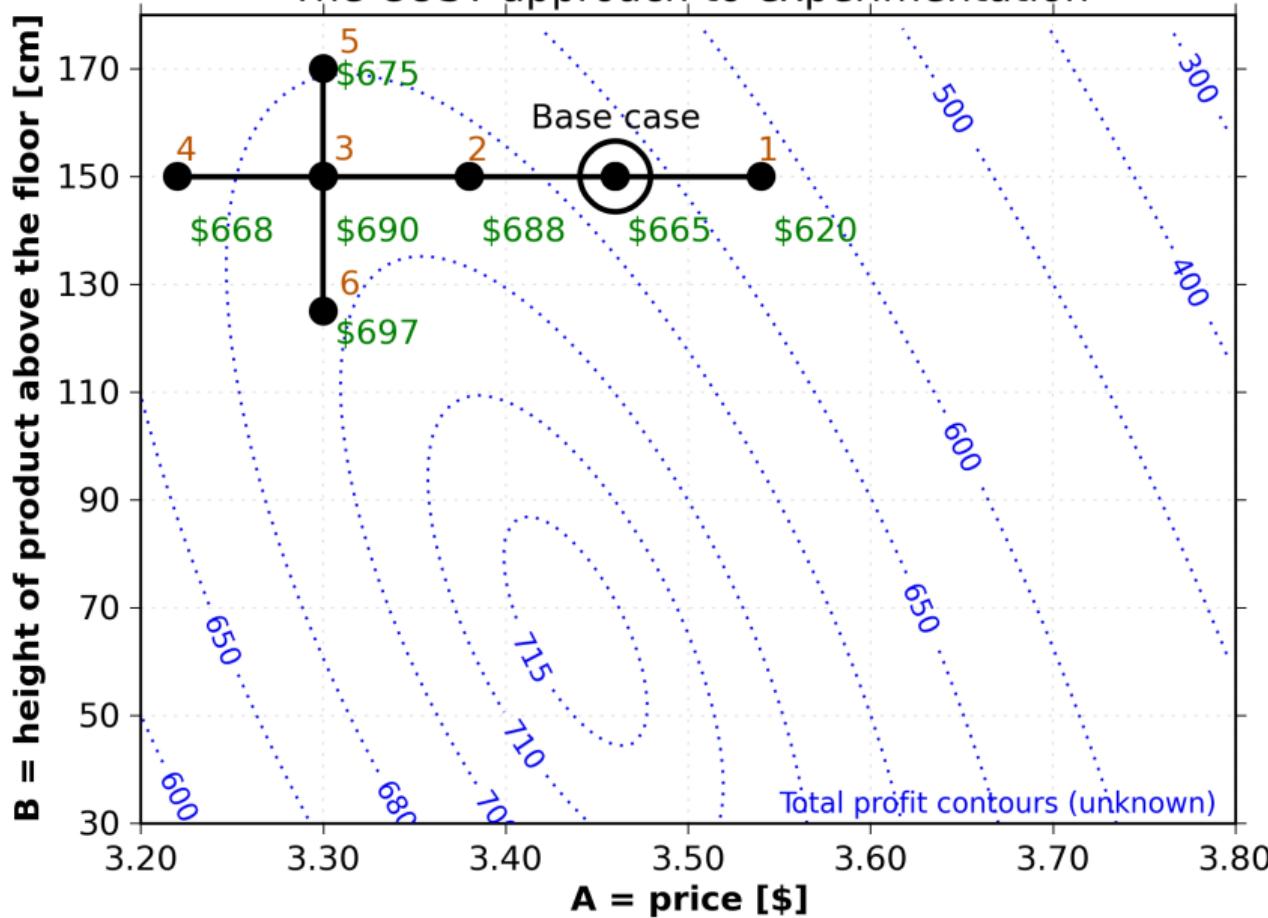
The COST approach to experimentation



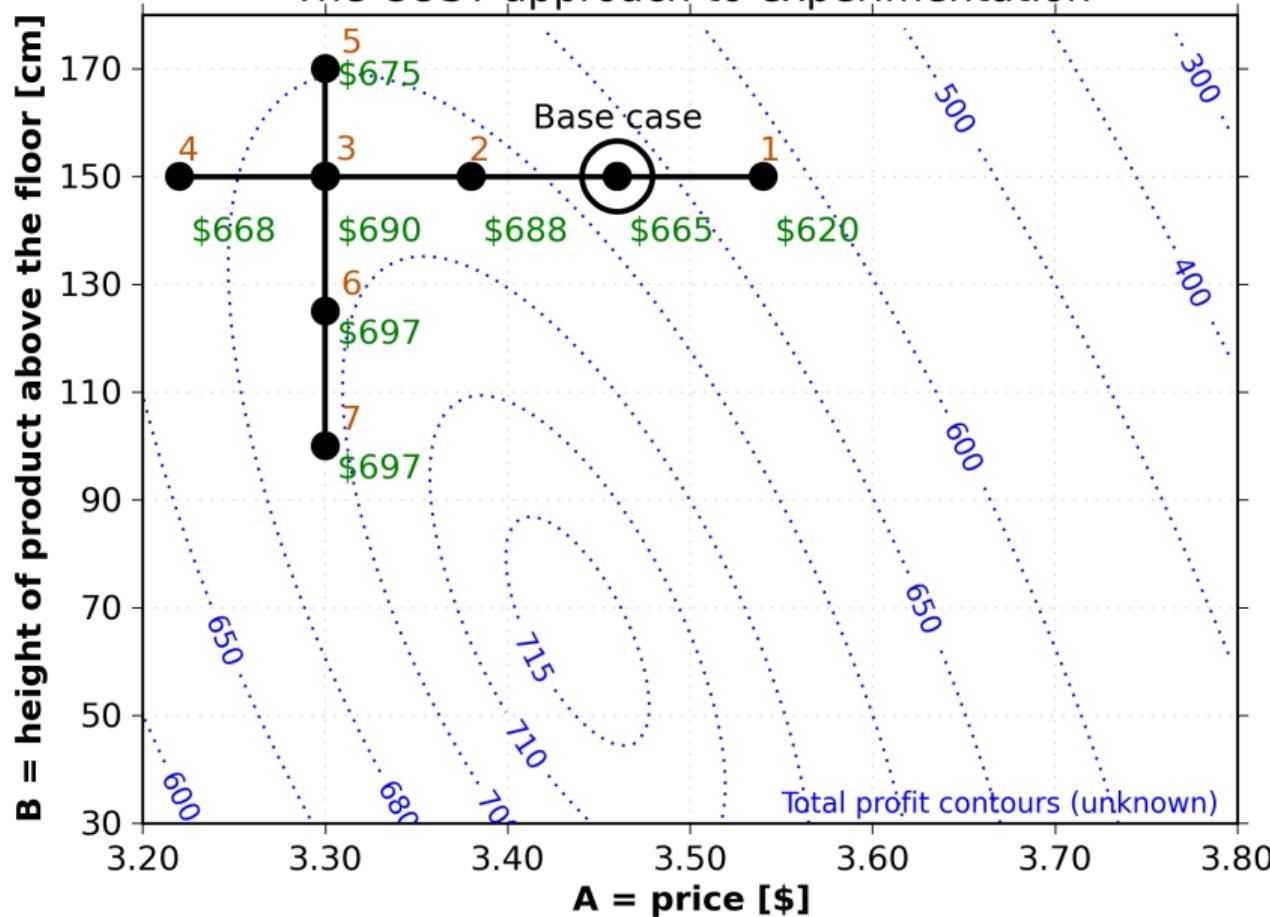
The COST approach to experimentation



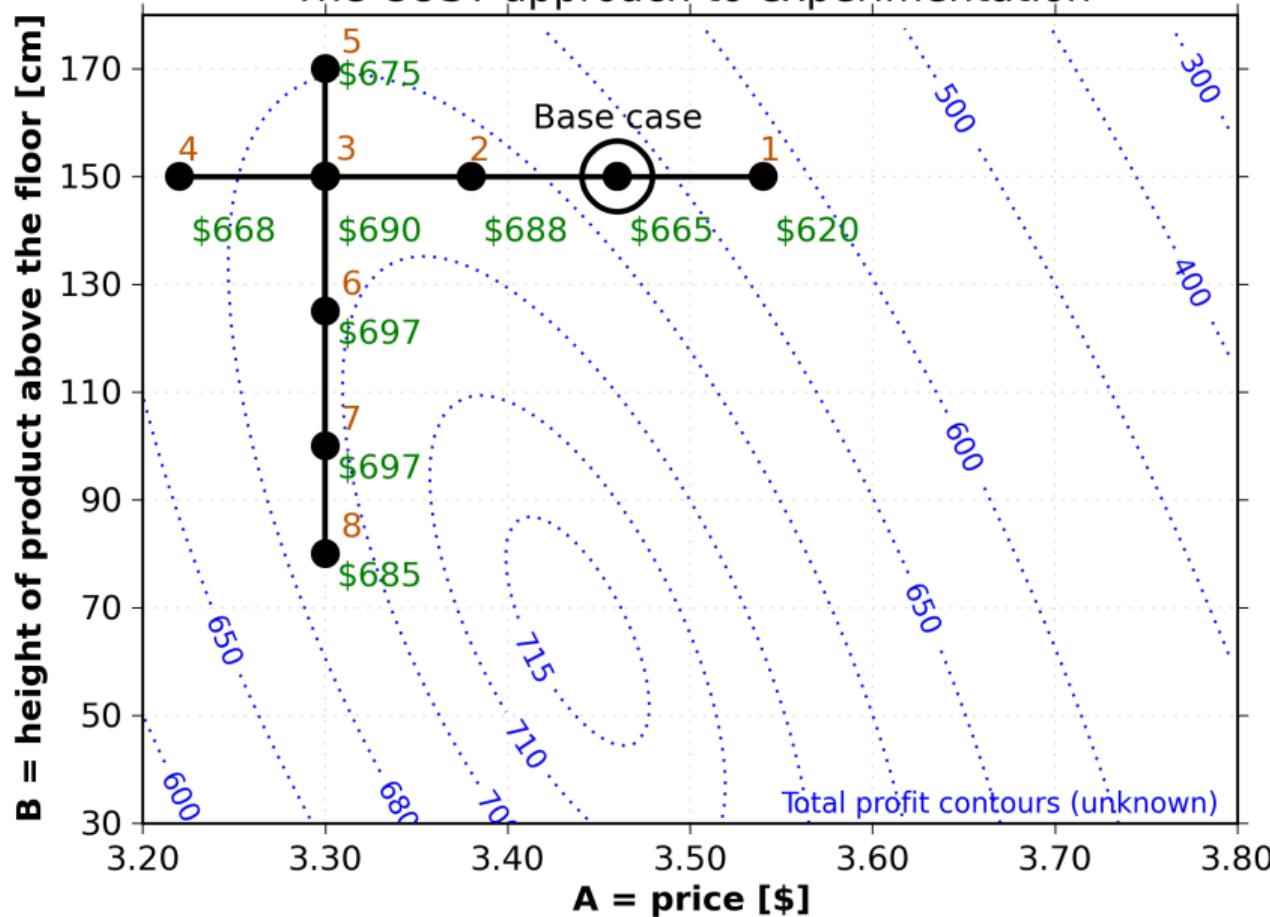
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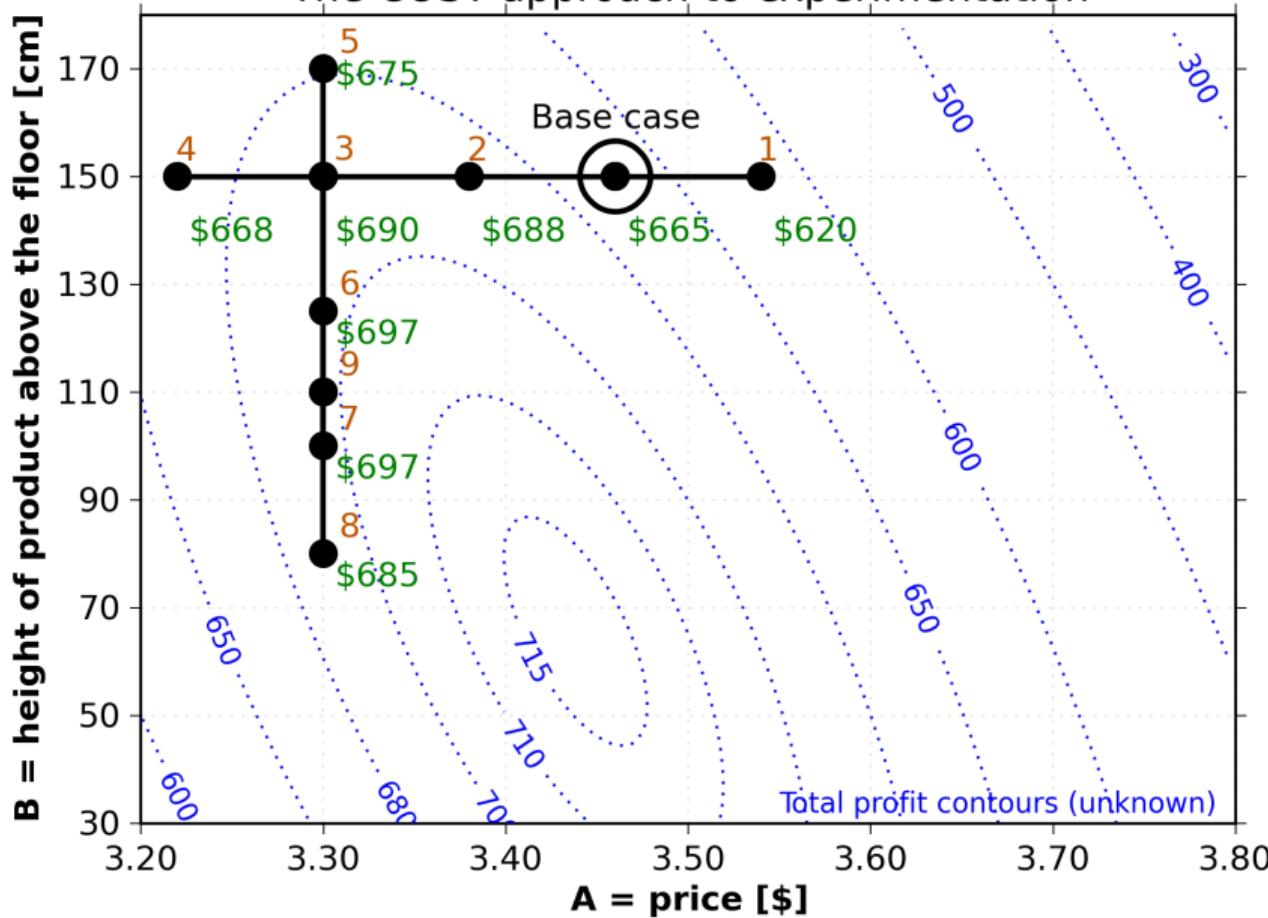
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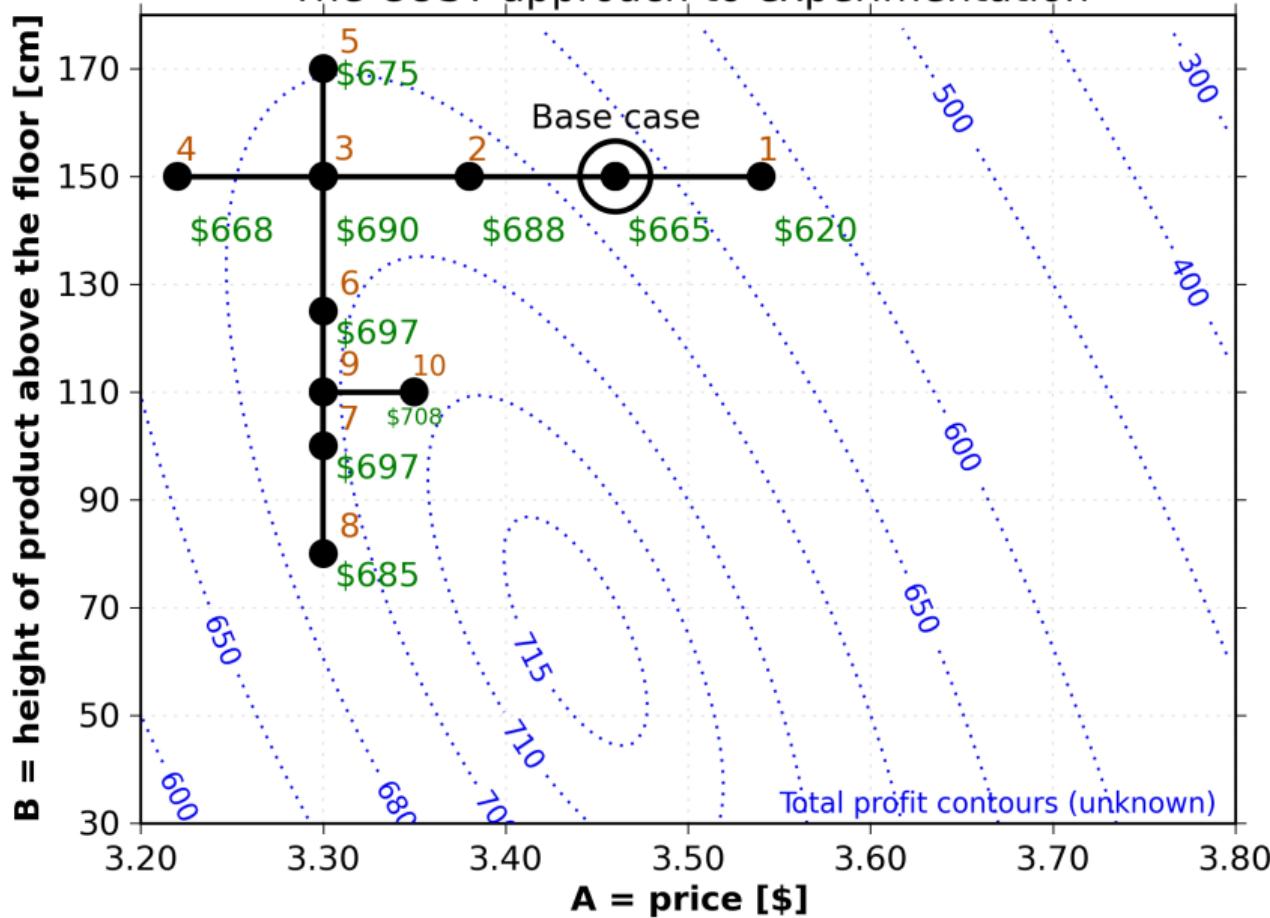
The COST approach to experimentation



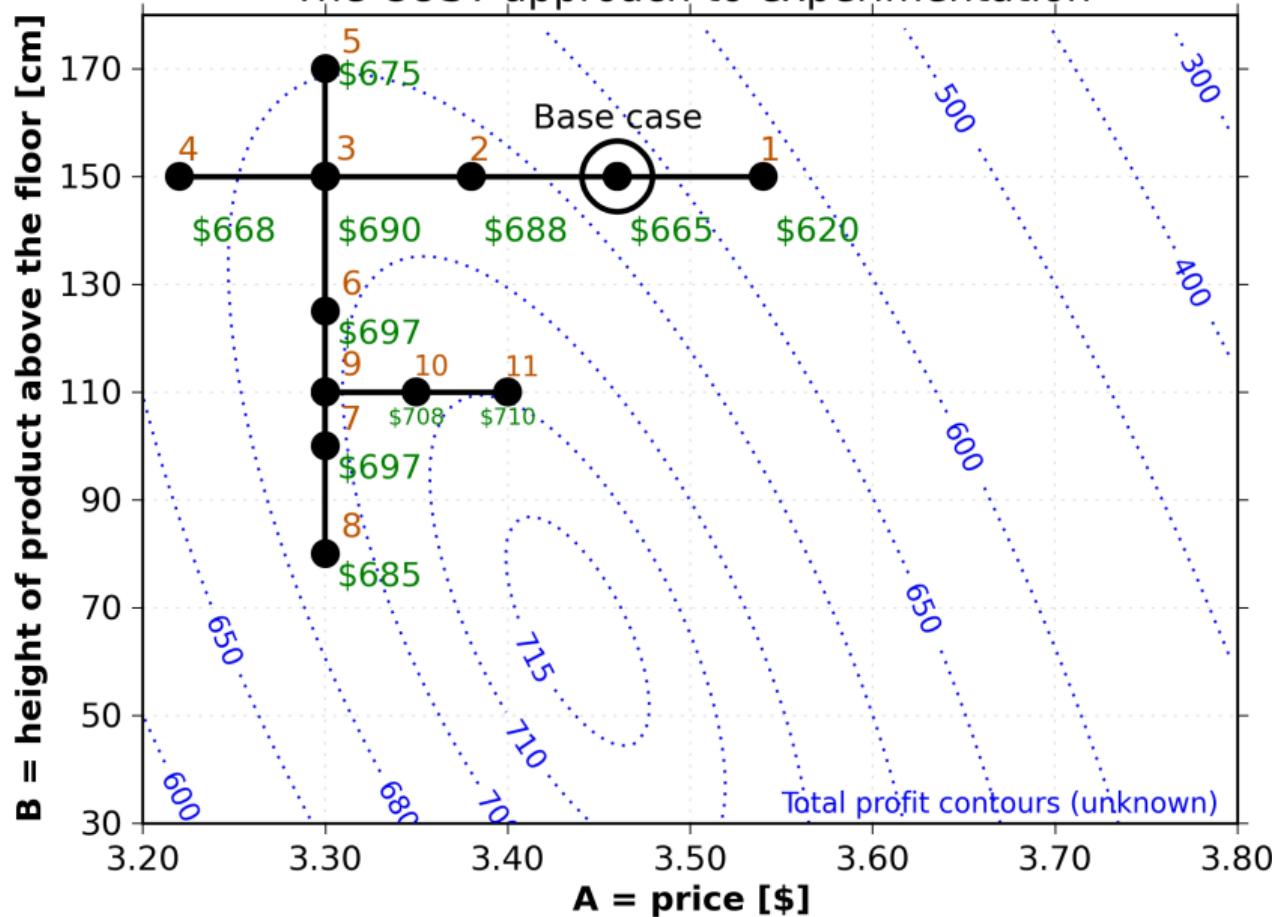
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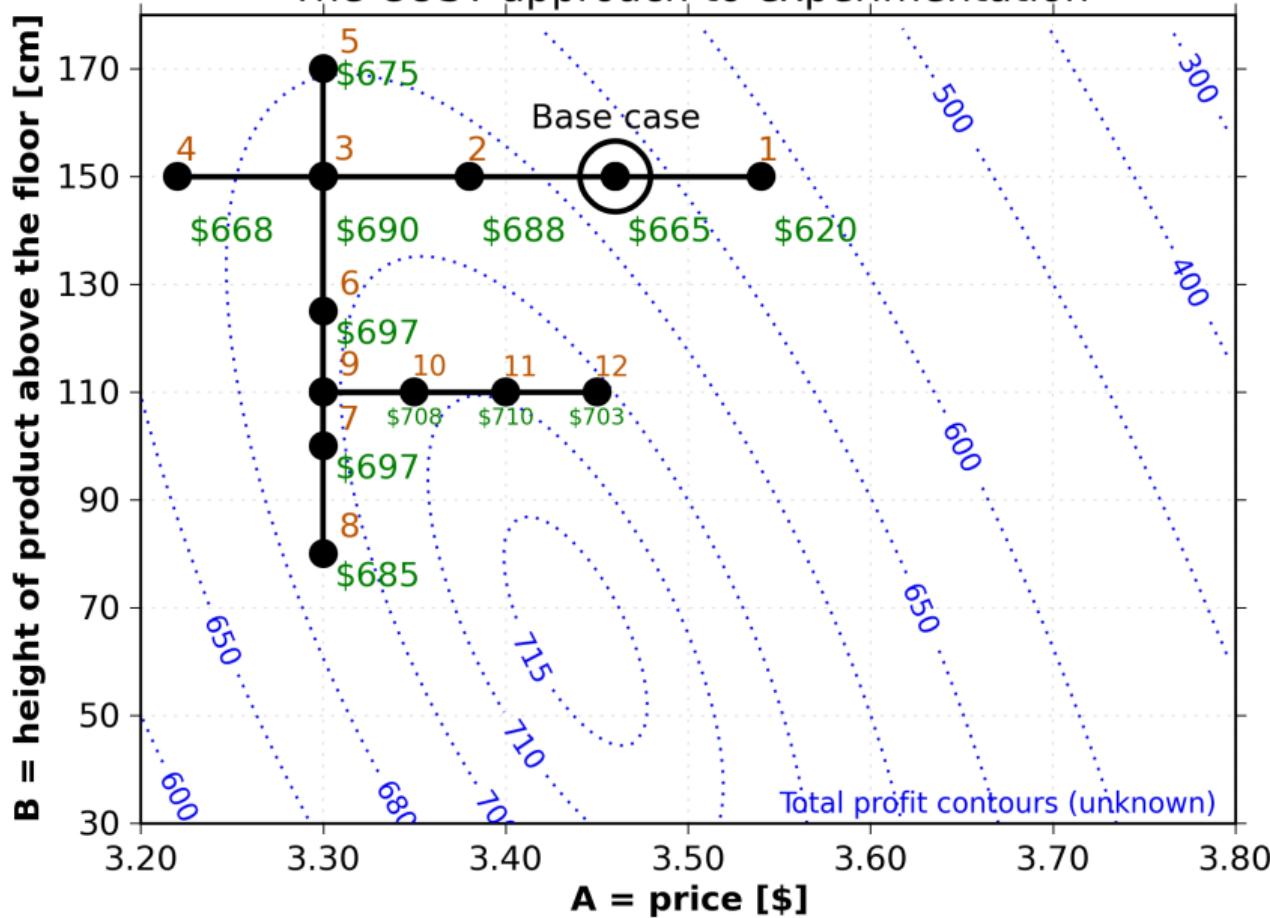
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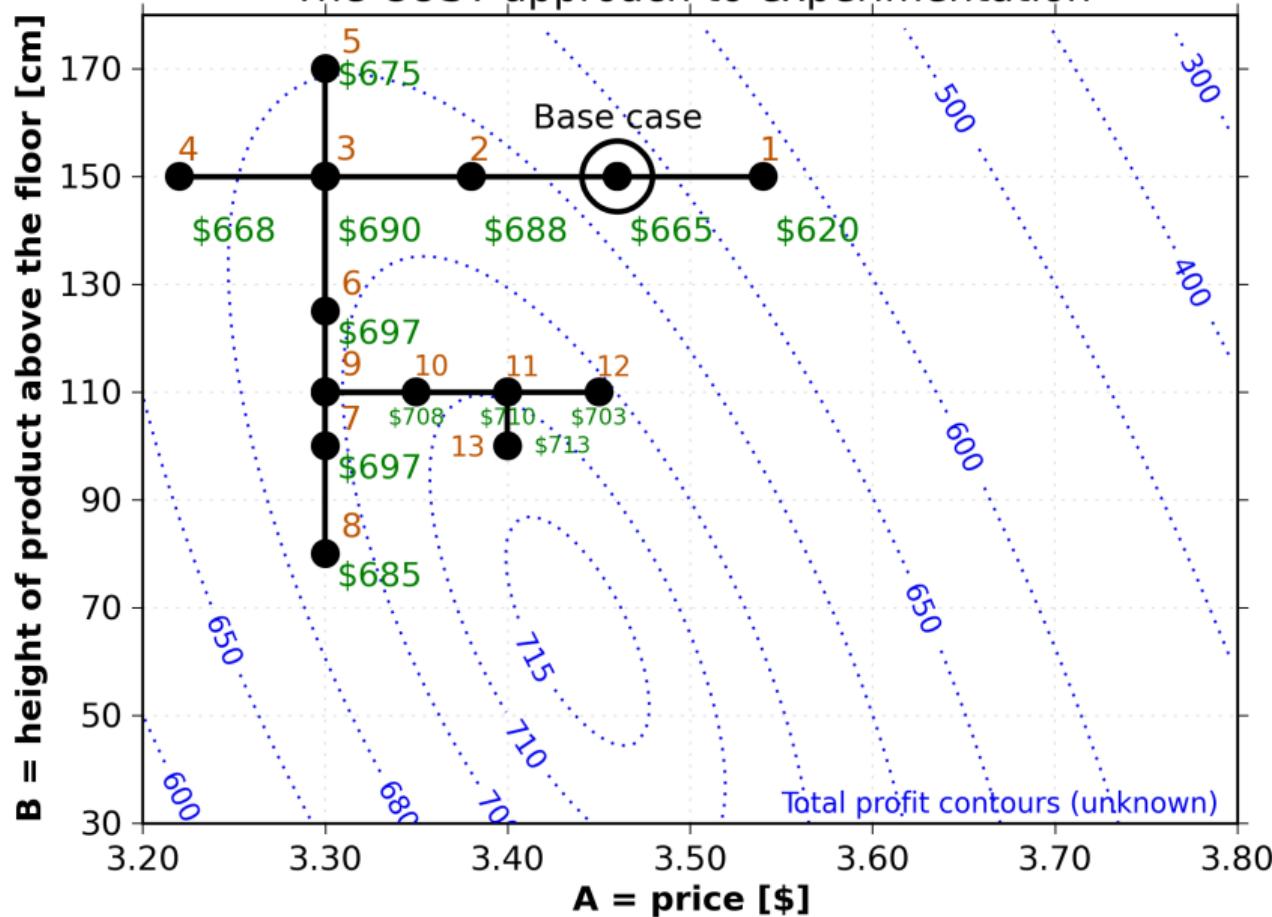
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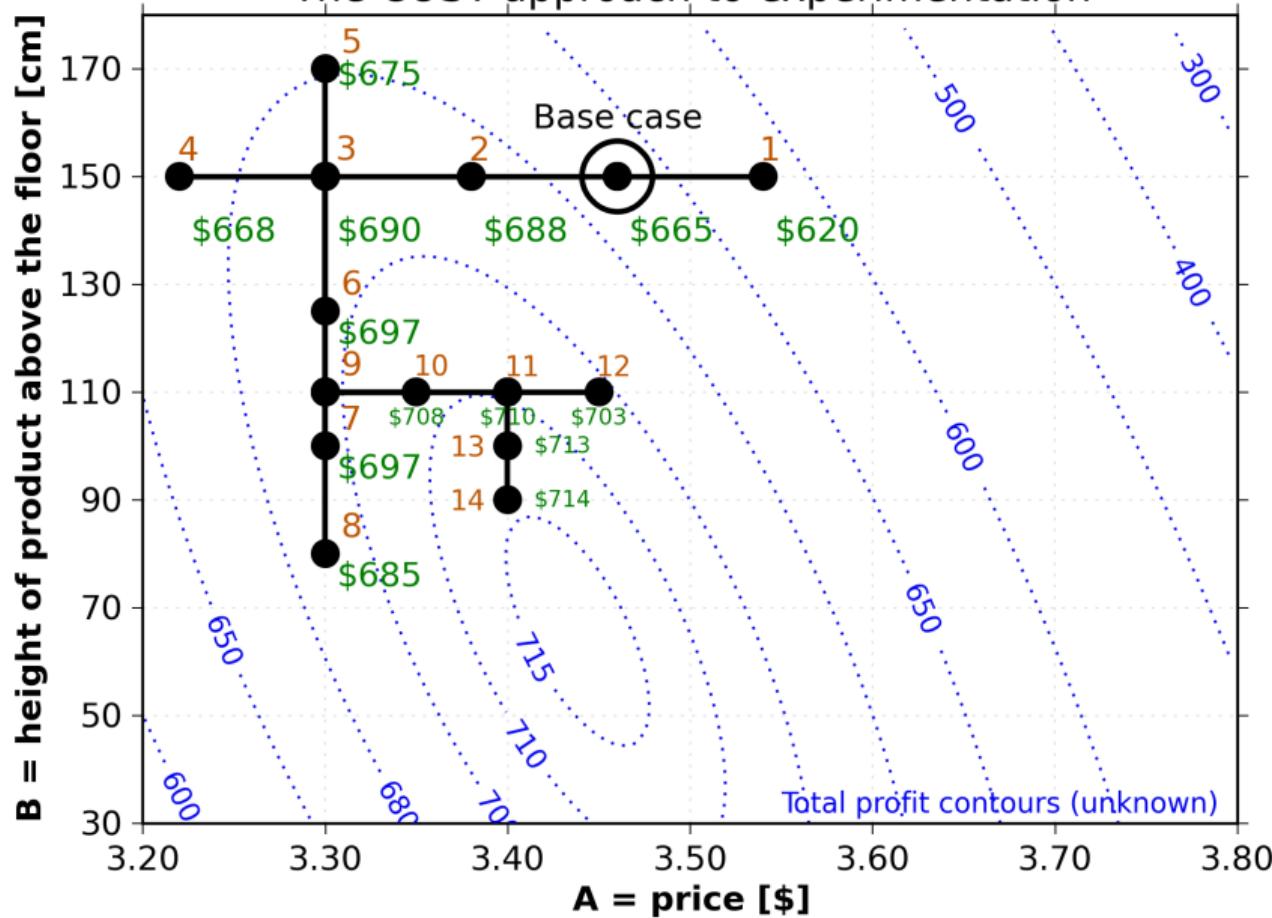
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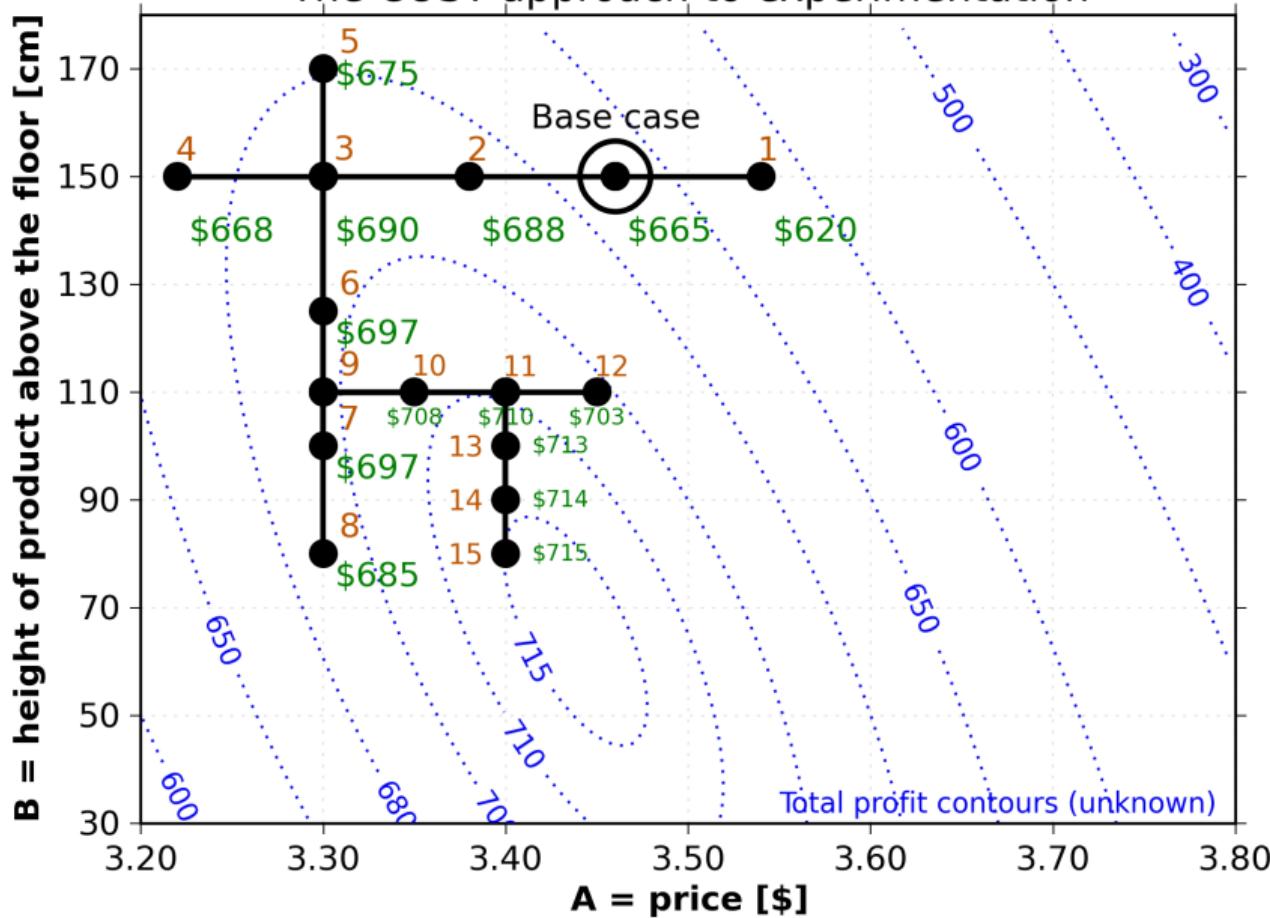
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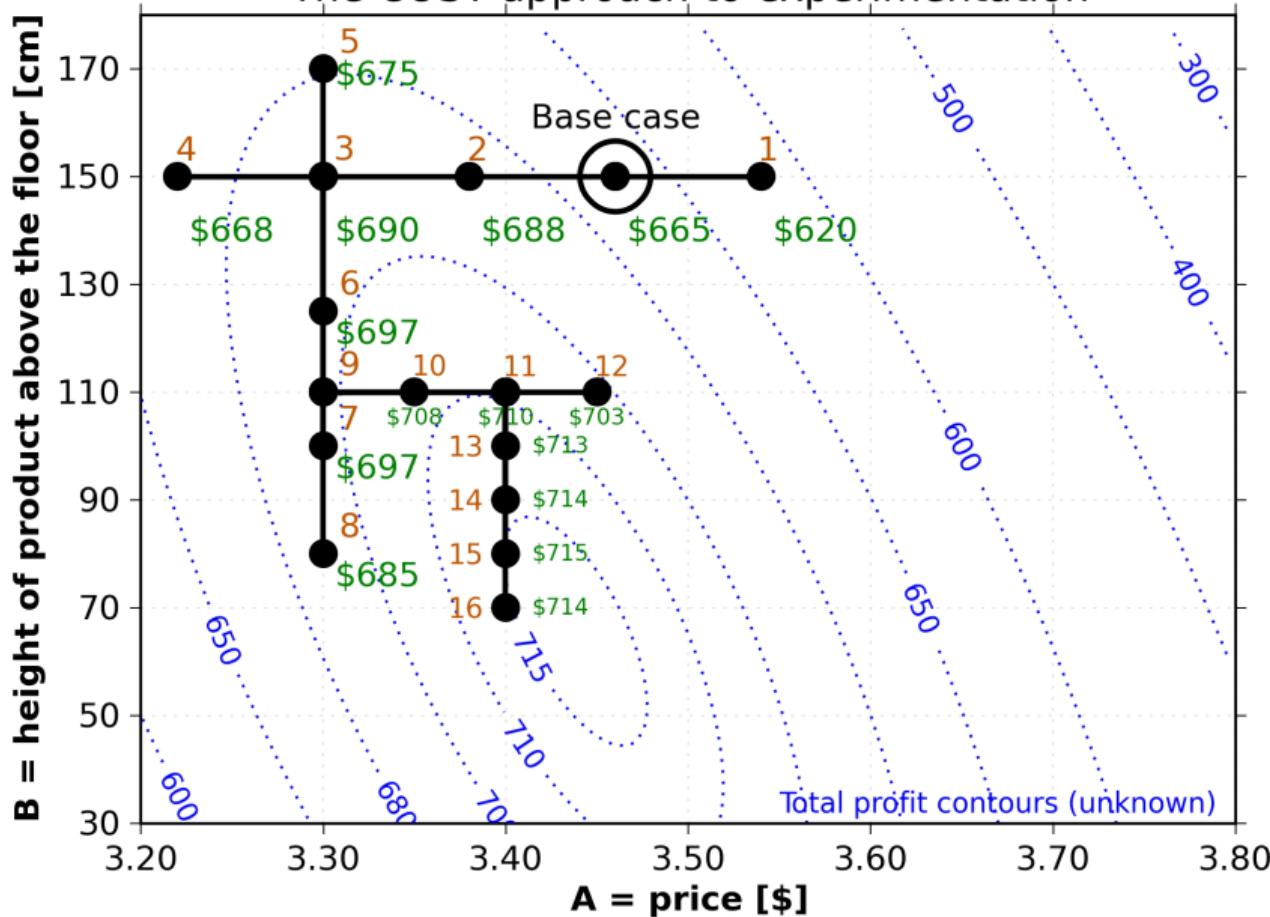
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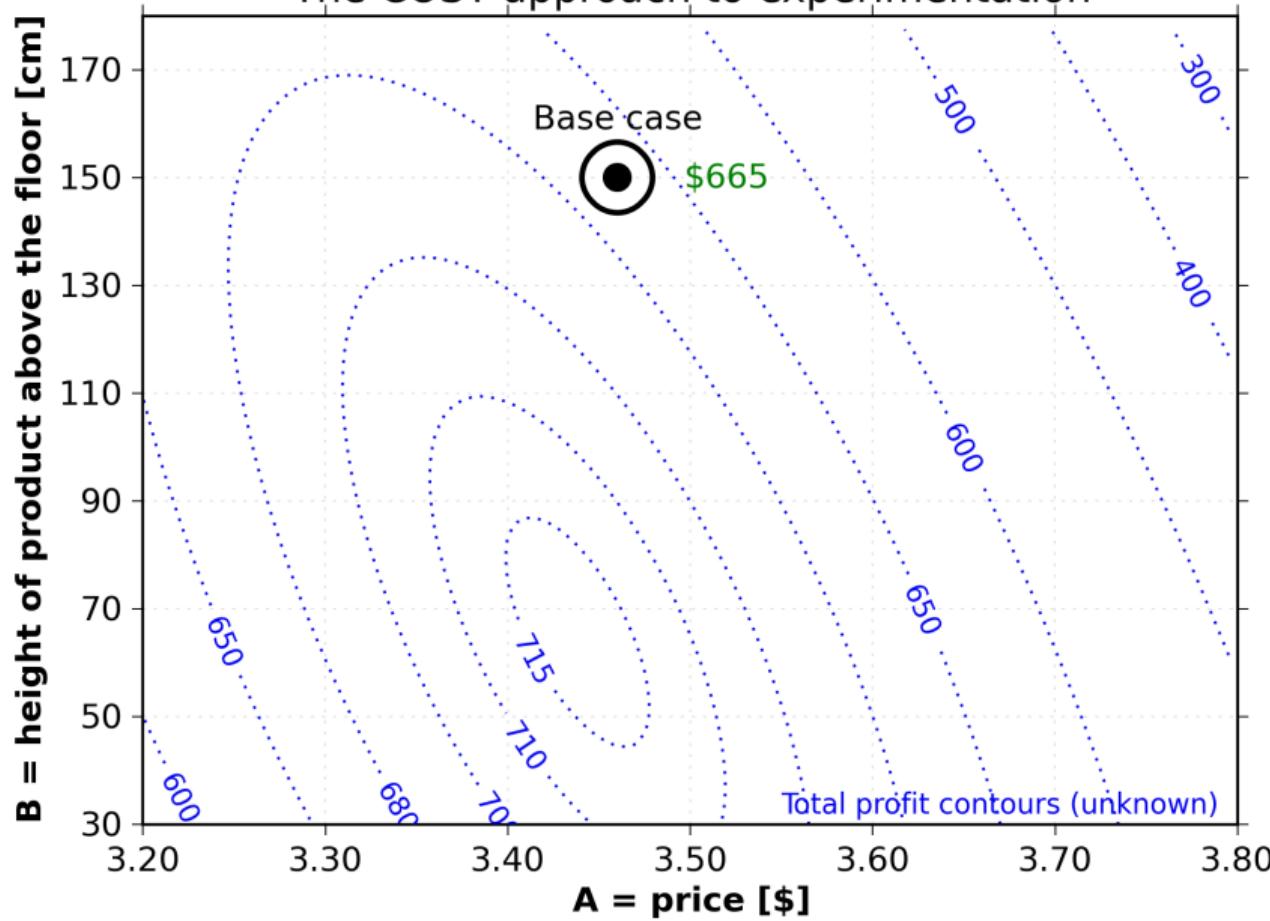
The COST approach to experimentation



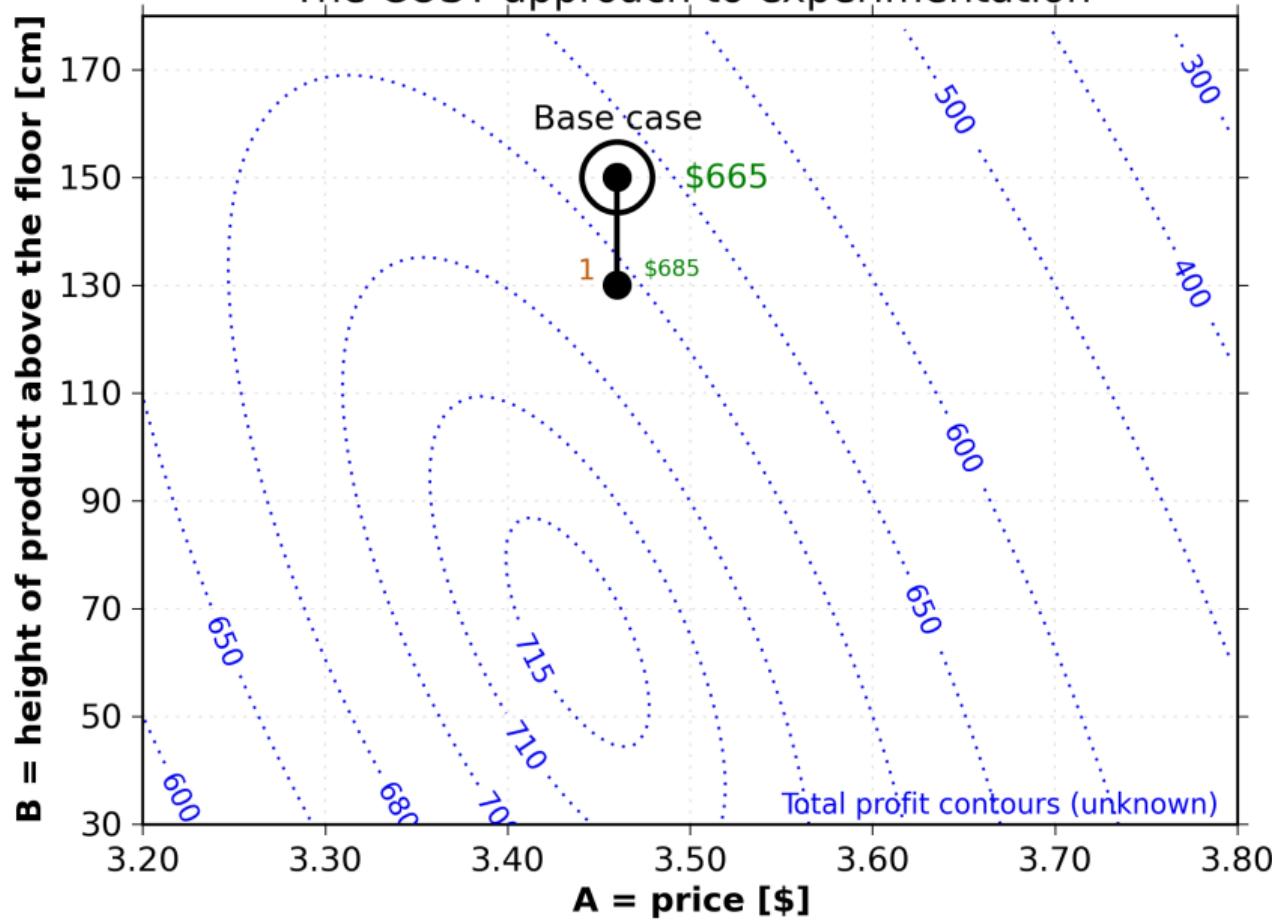
The COST approach to experimentation



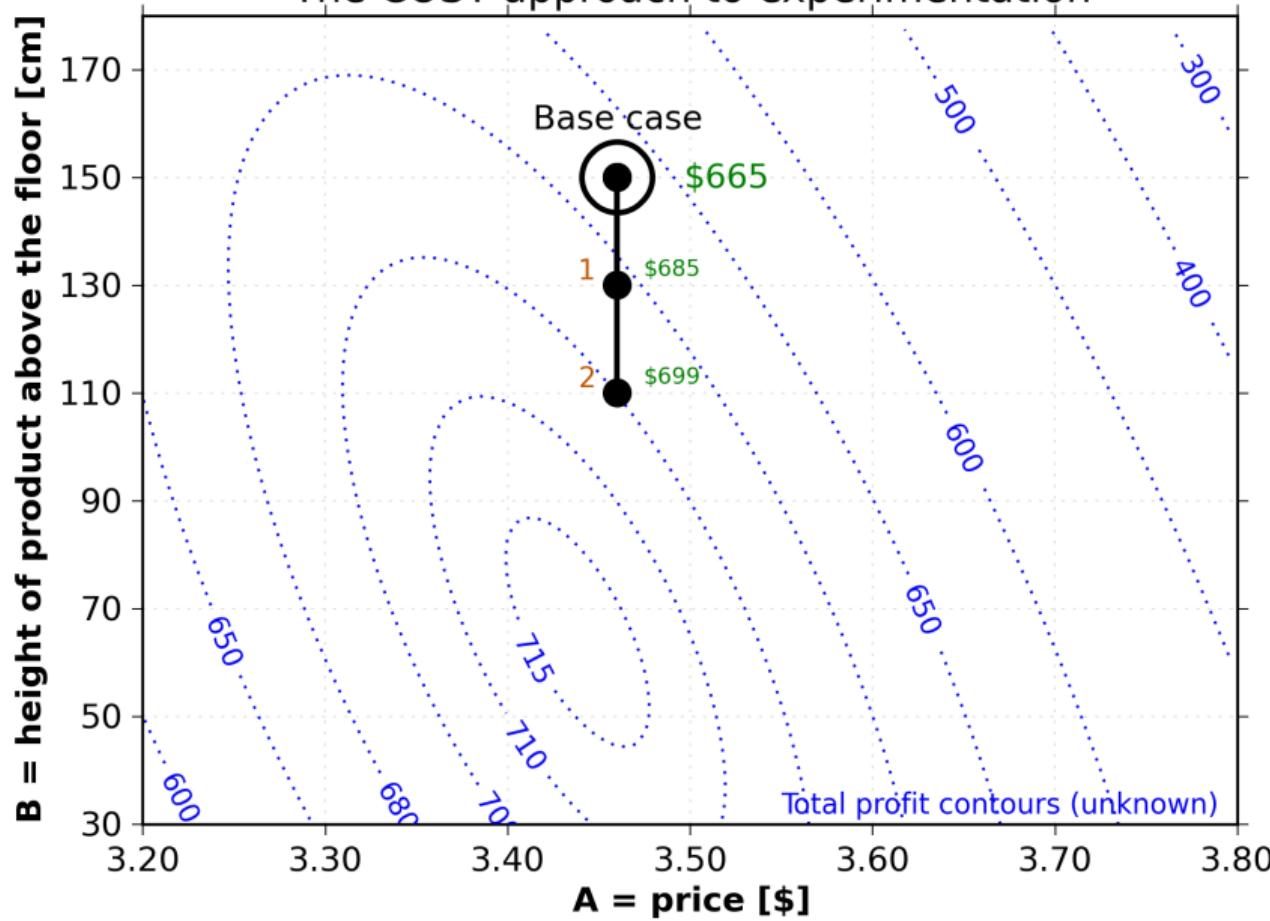
The COST approach to experimentation



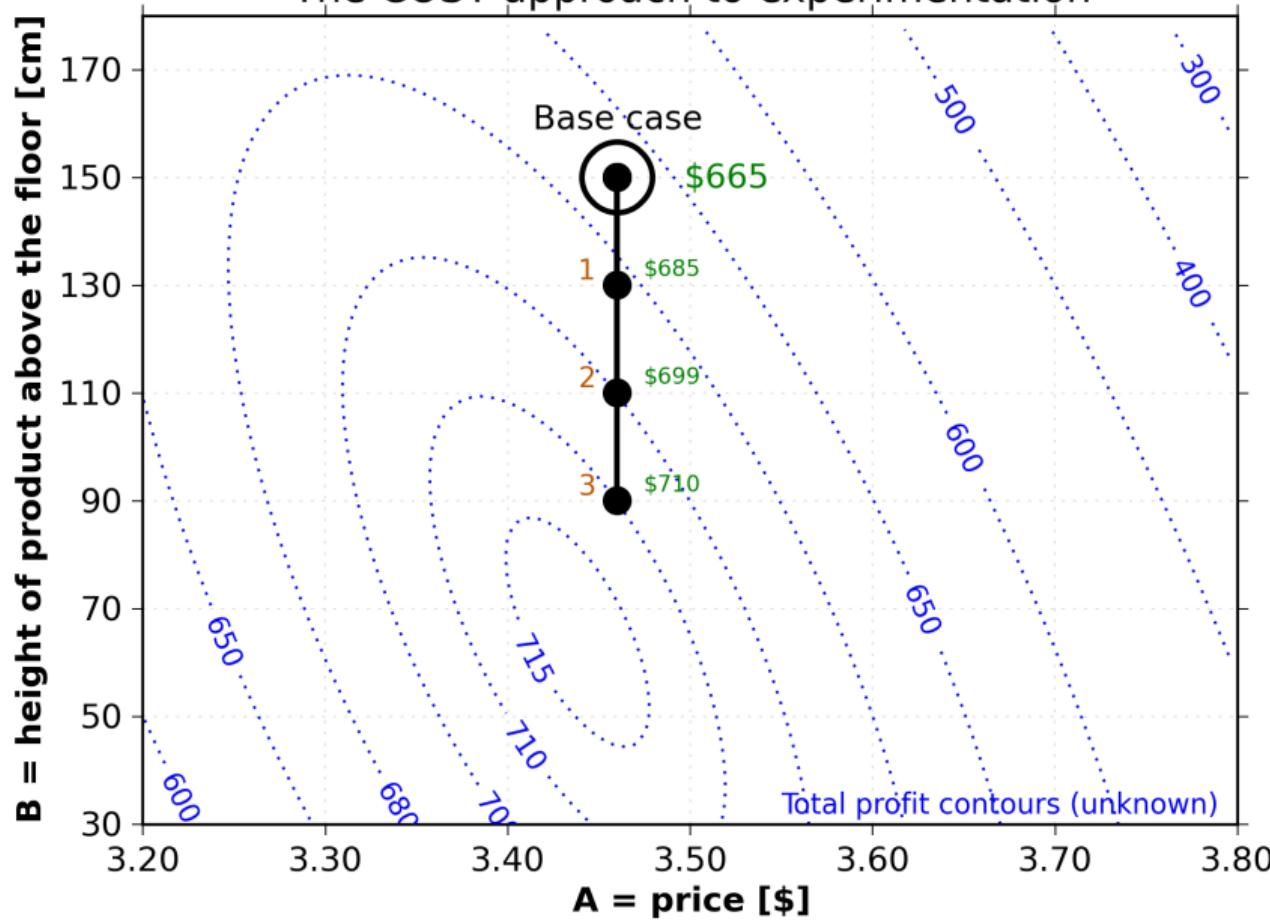
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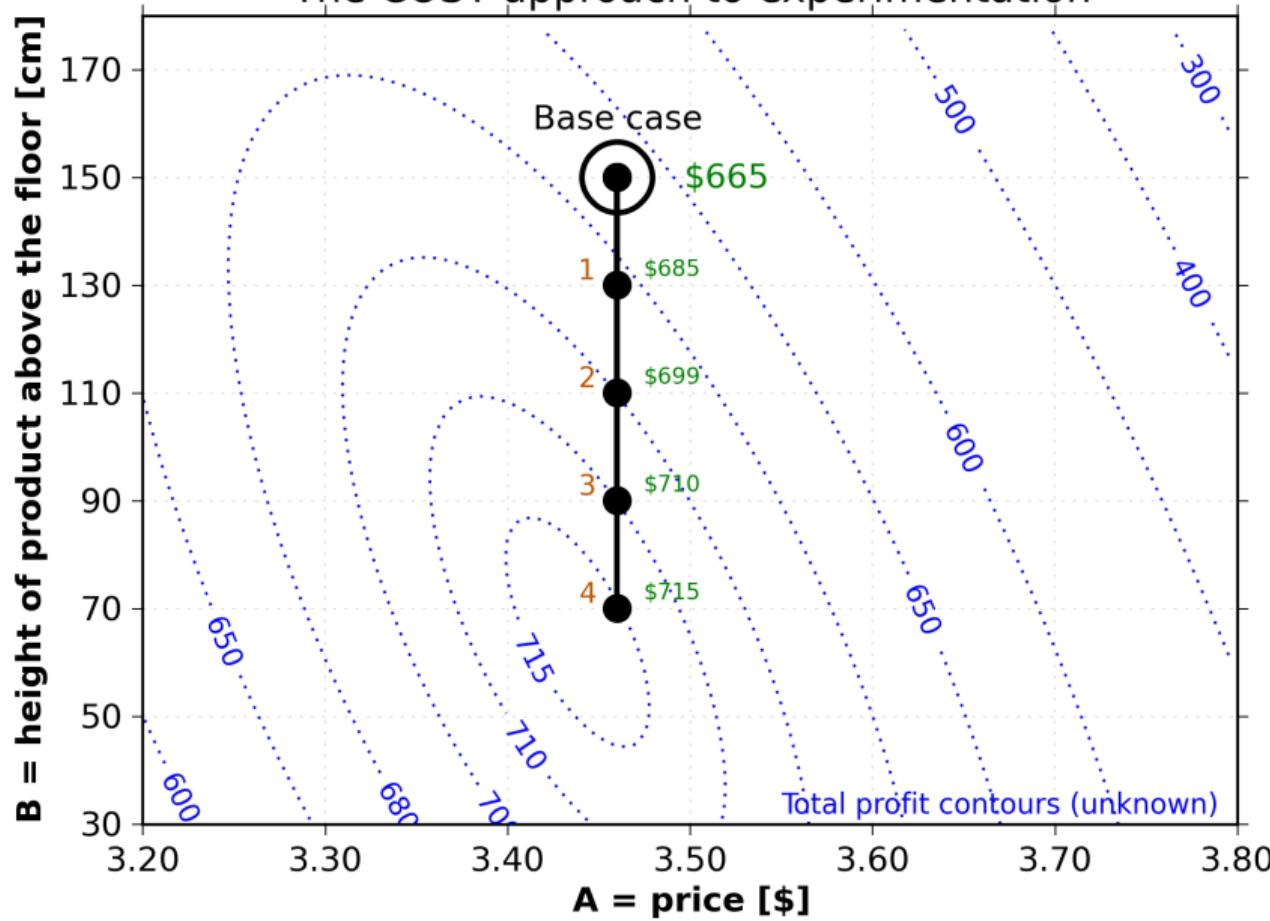
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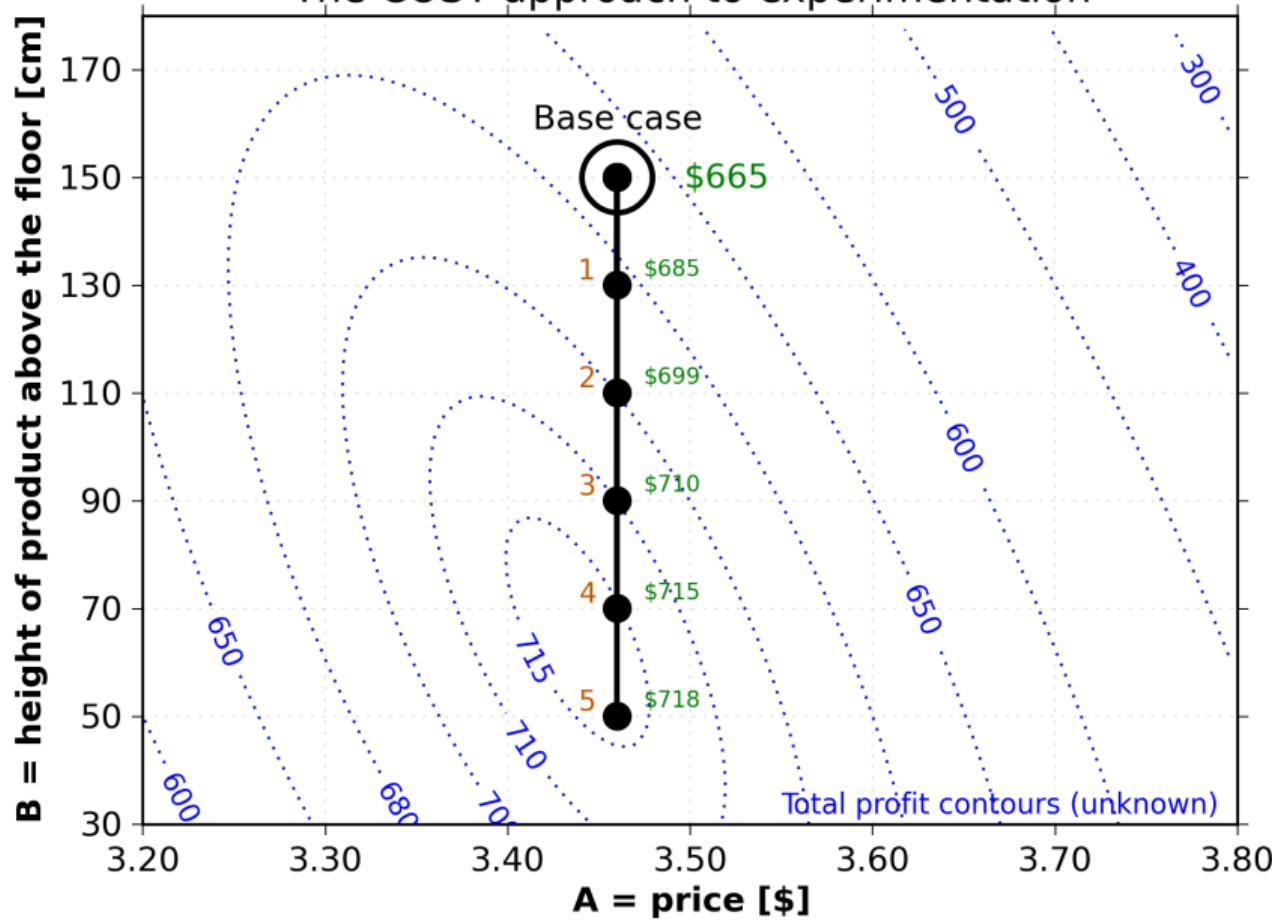
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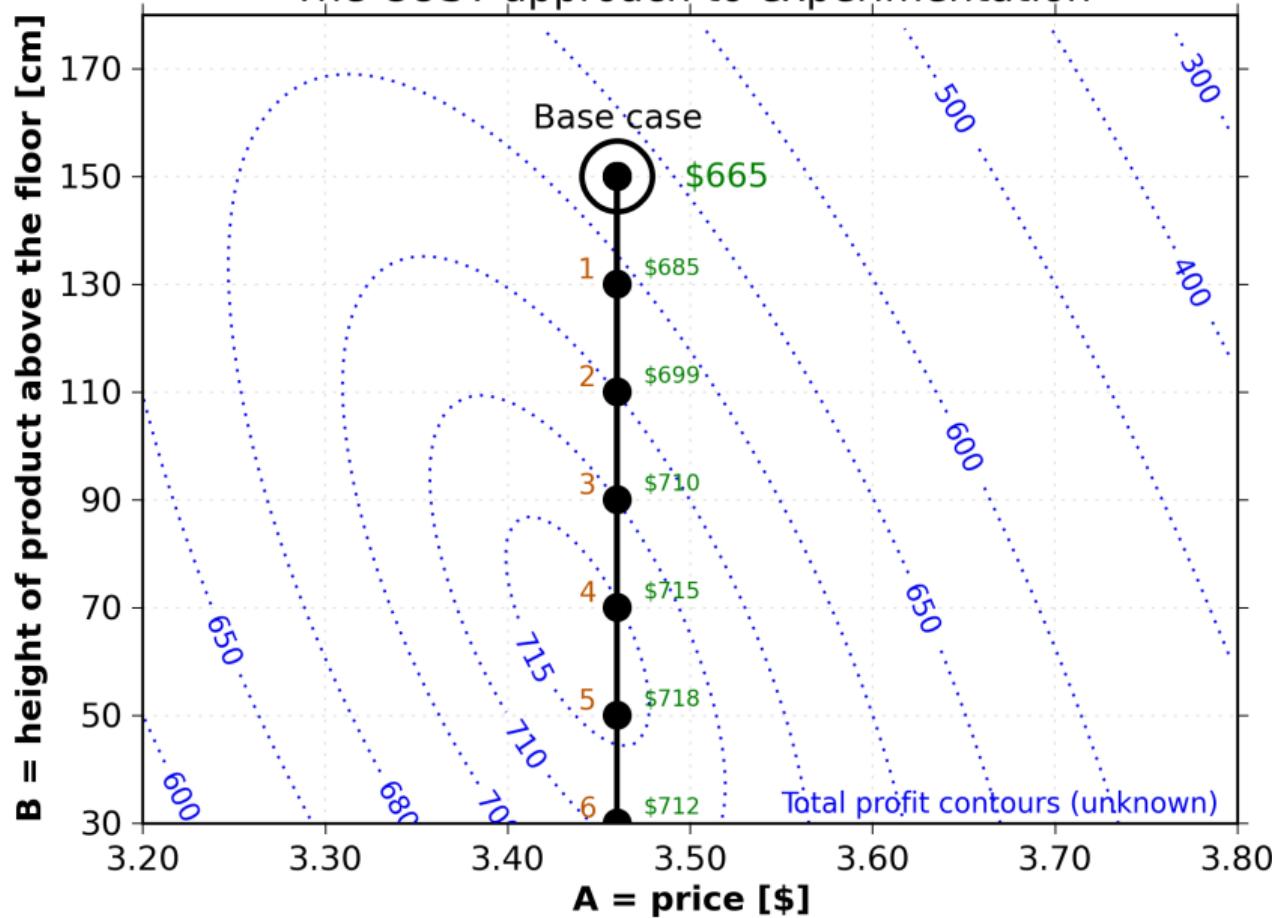
The COST approach to experimentation



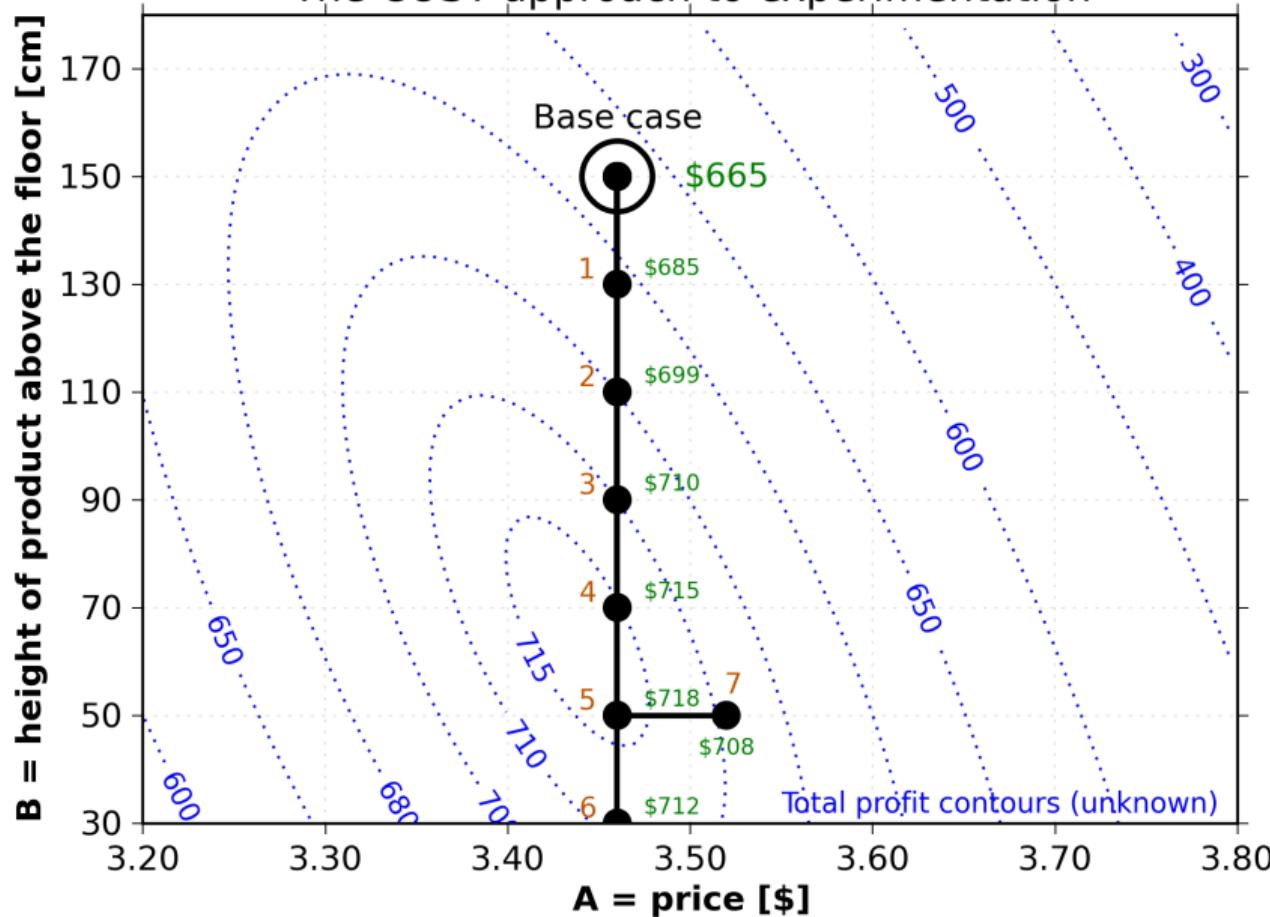
The COST approach to experimentation



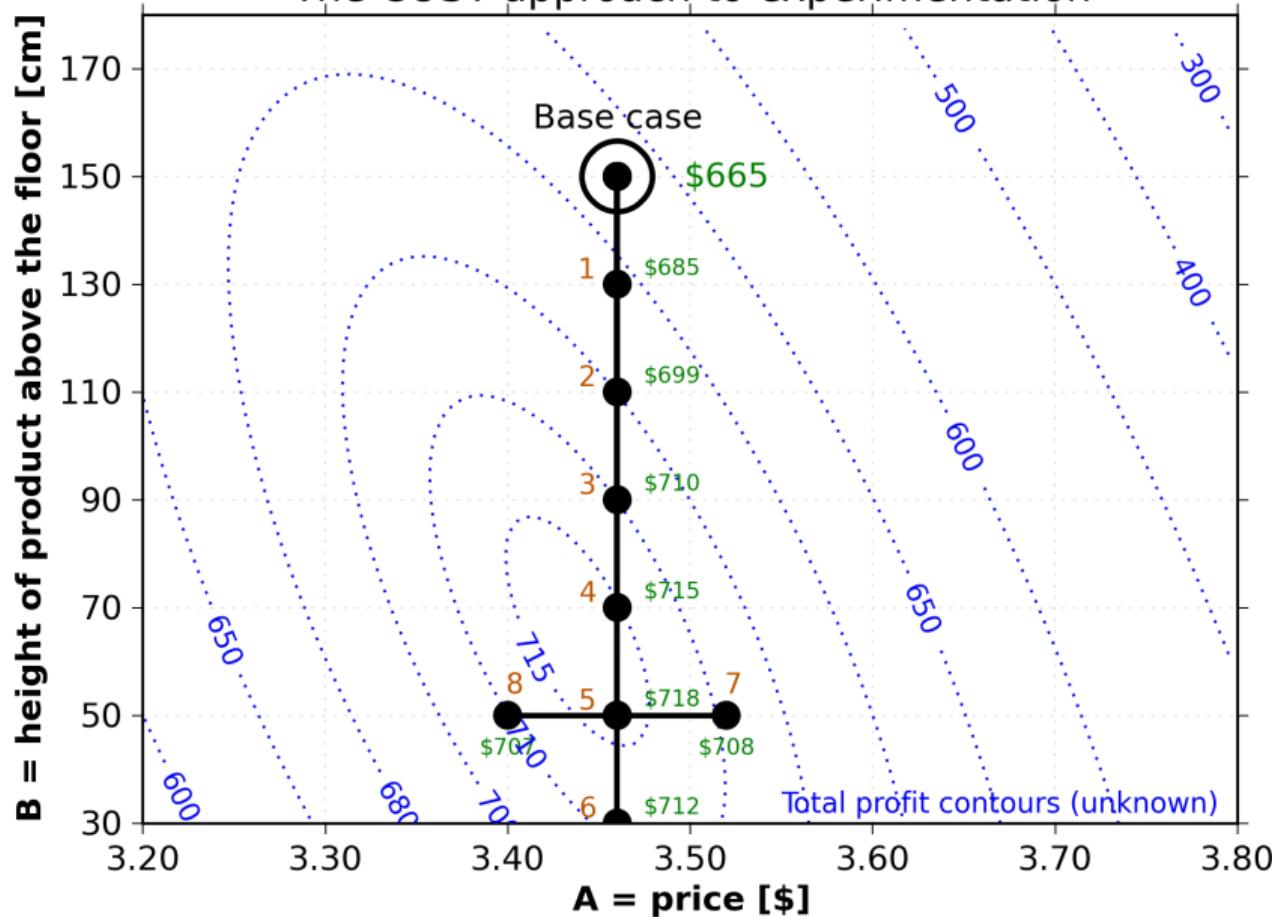
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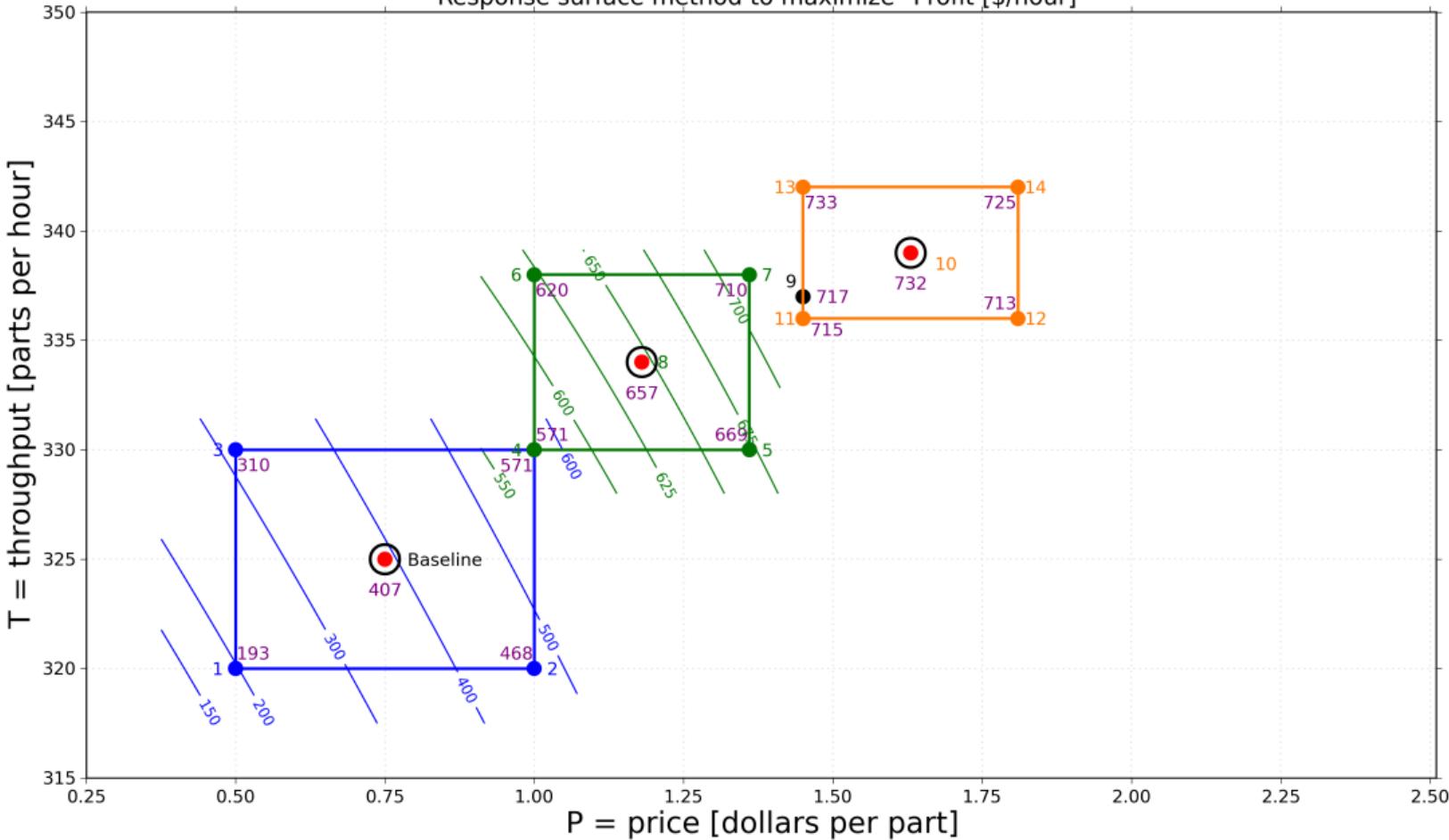
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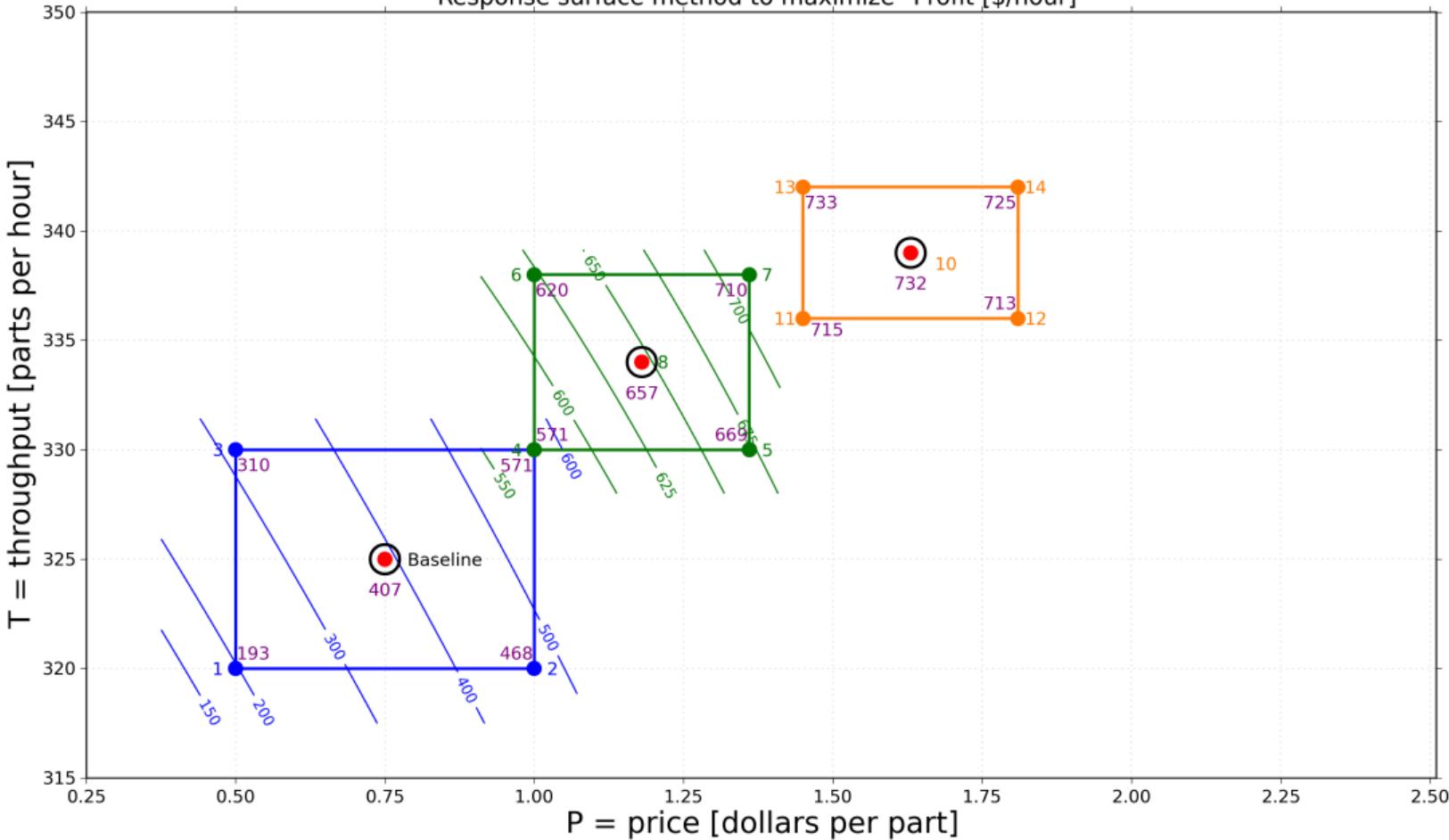
The COST approach to experimentation



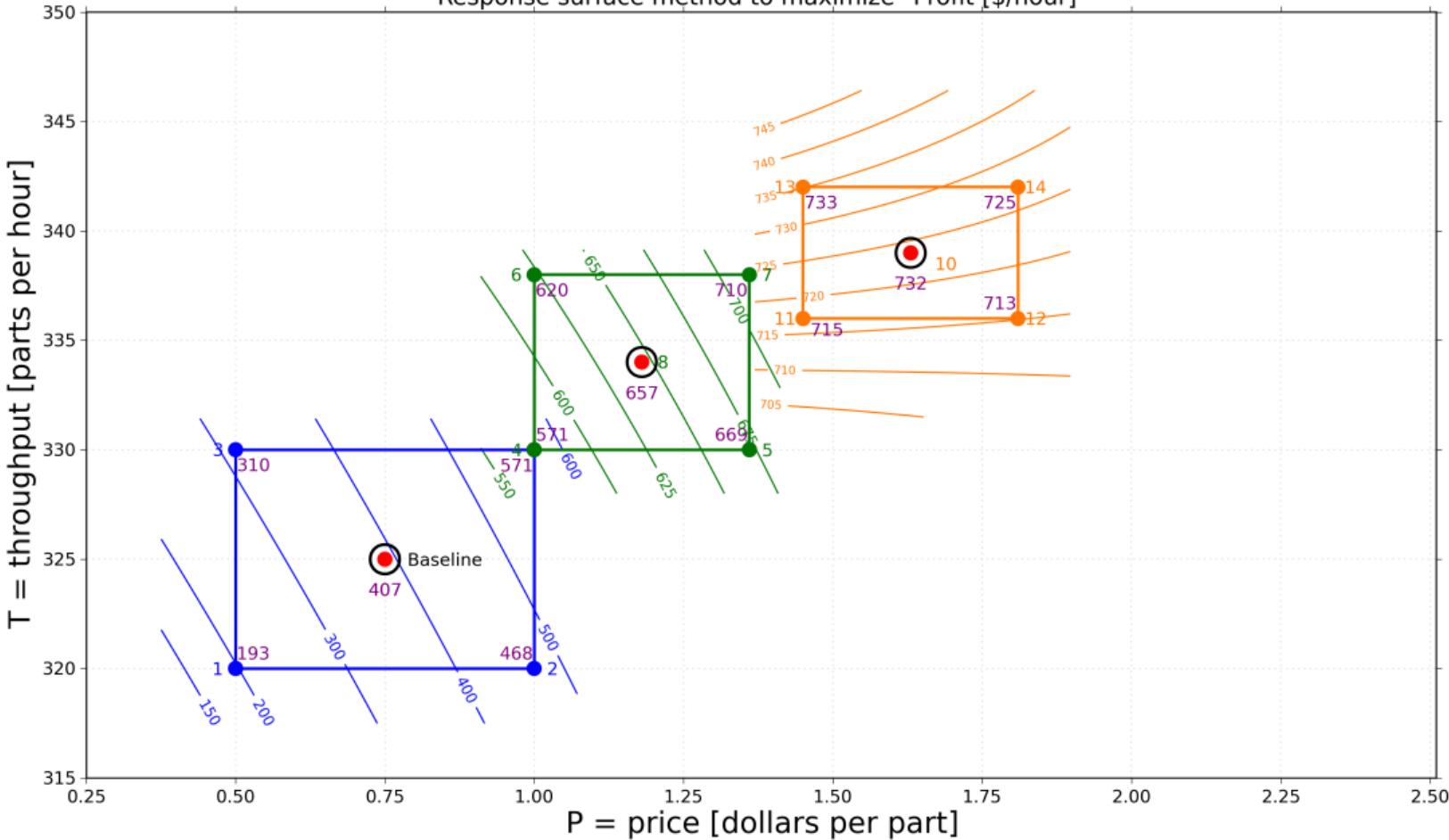
Response surface method to maximize "Profit [\$/hour]"



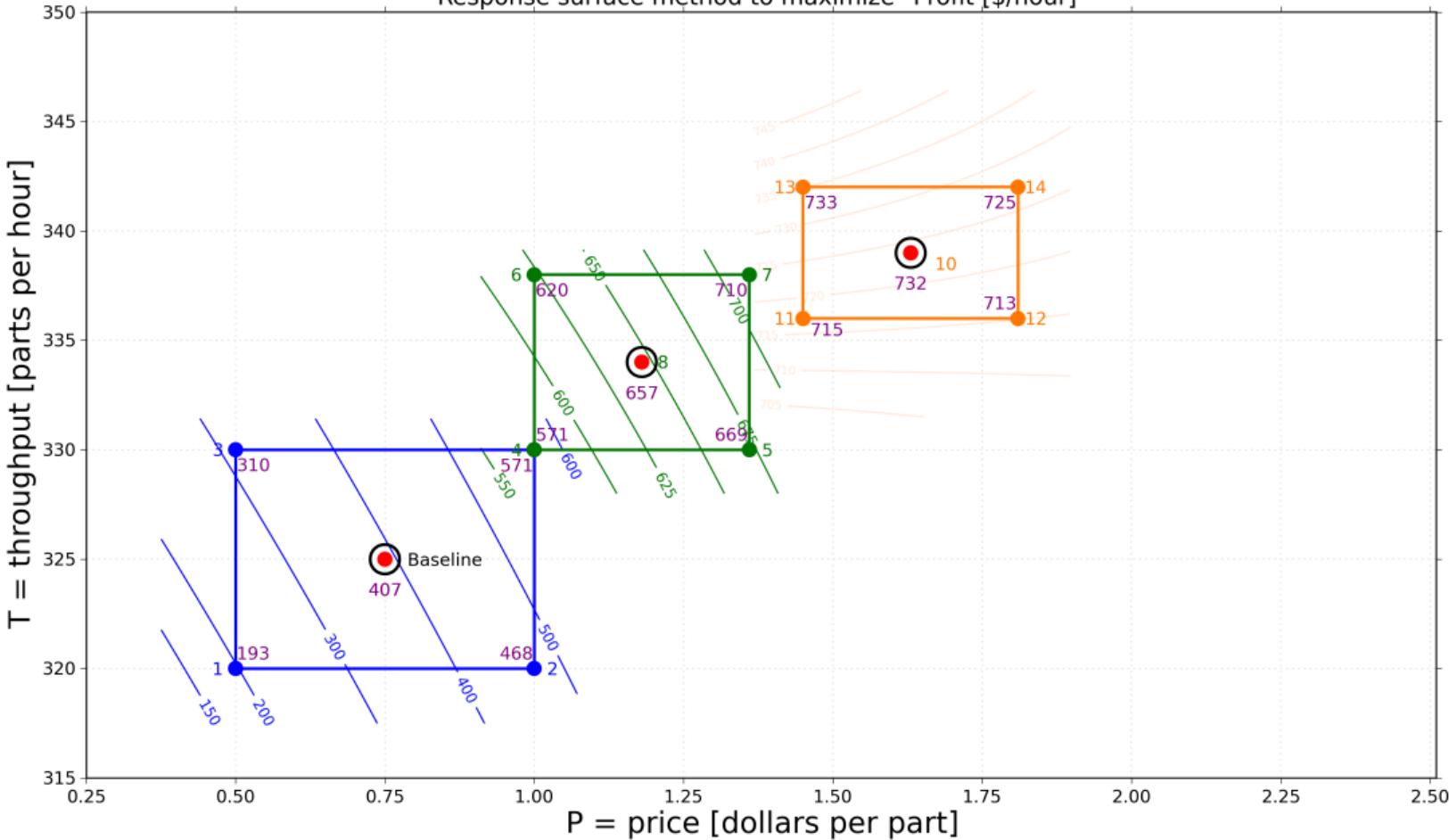
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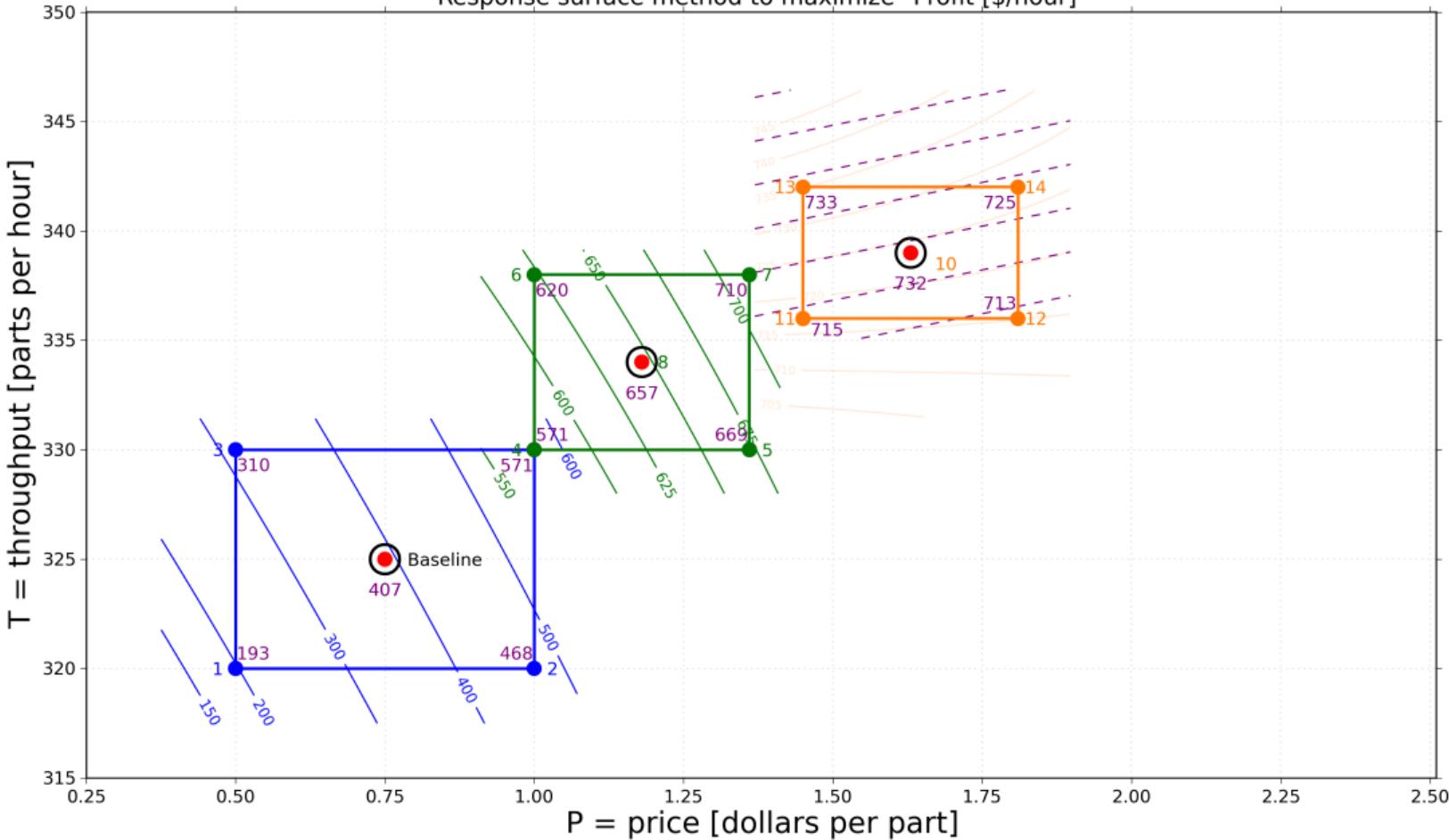
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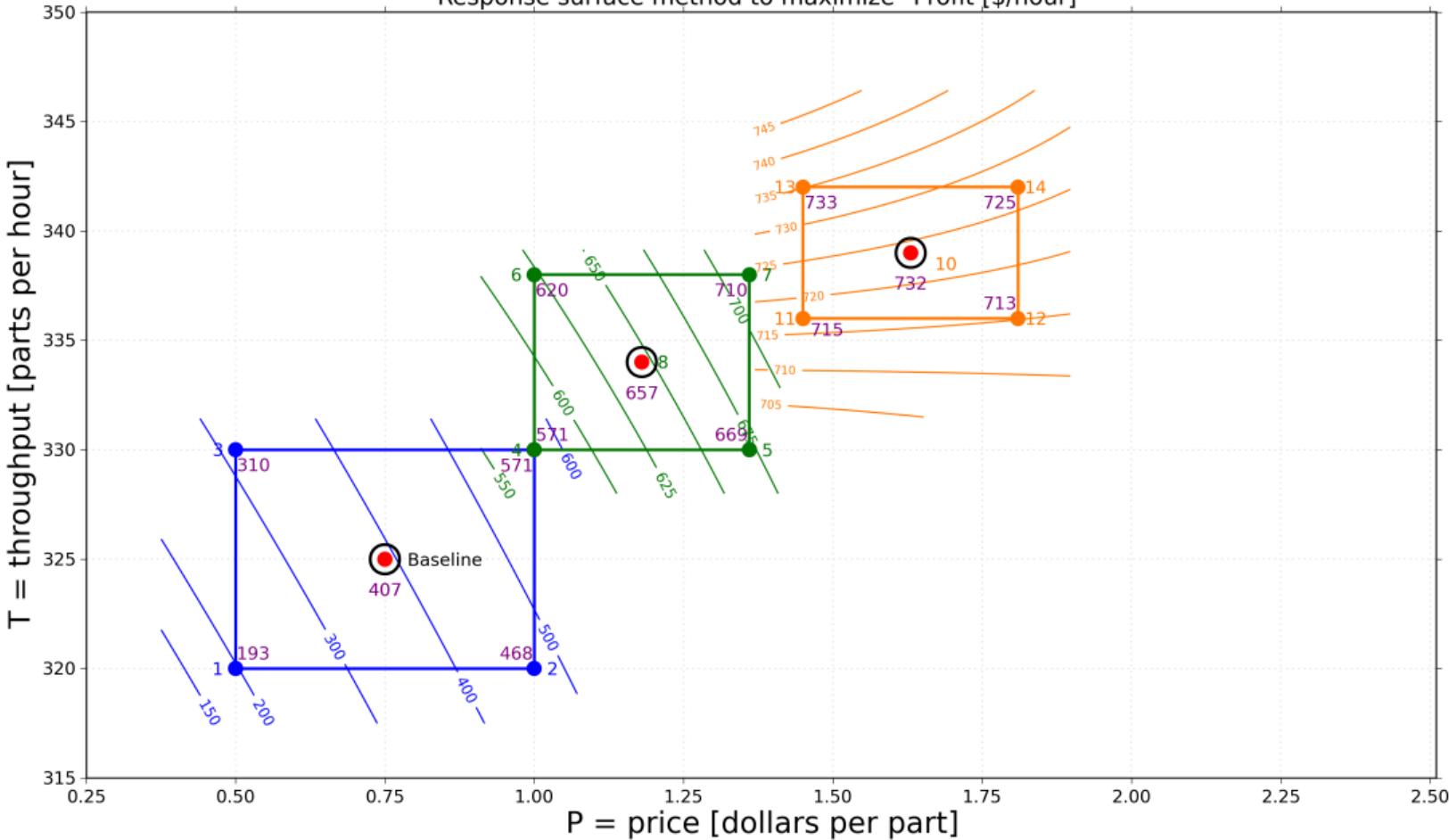
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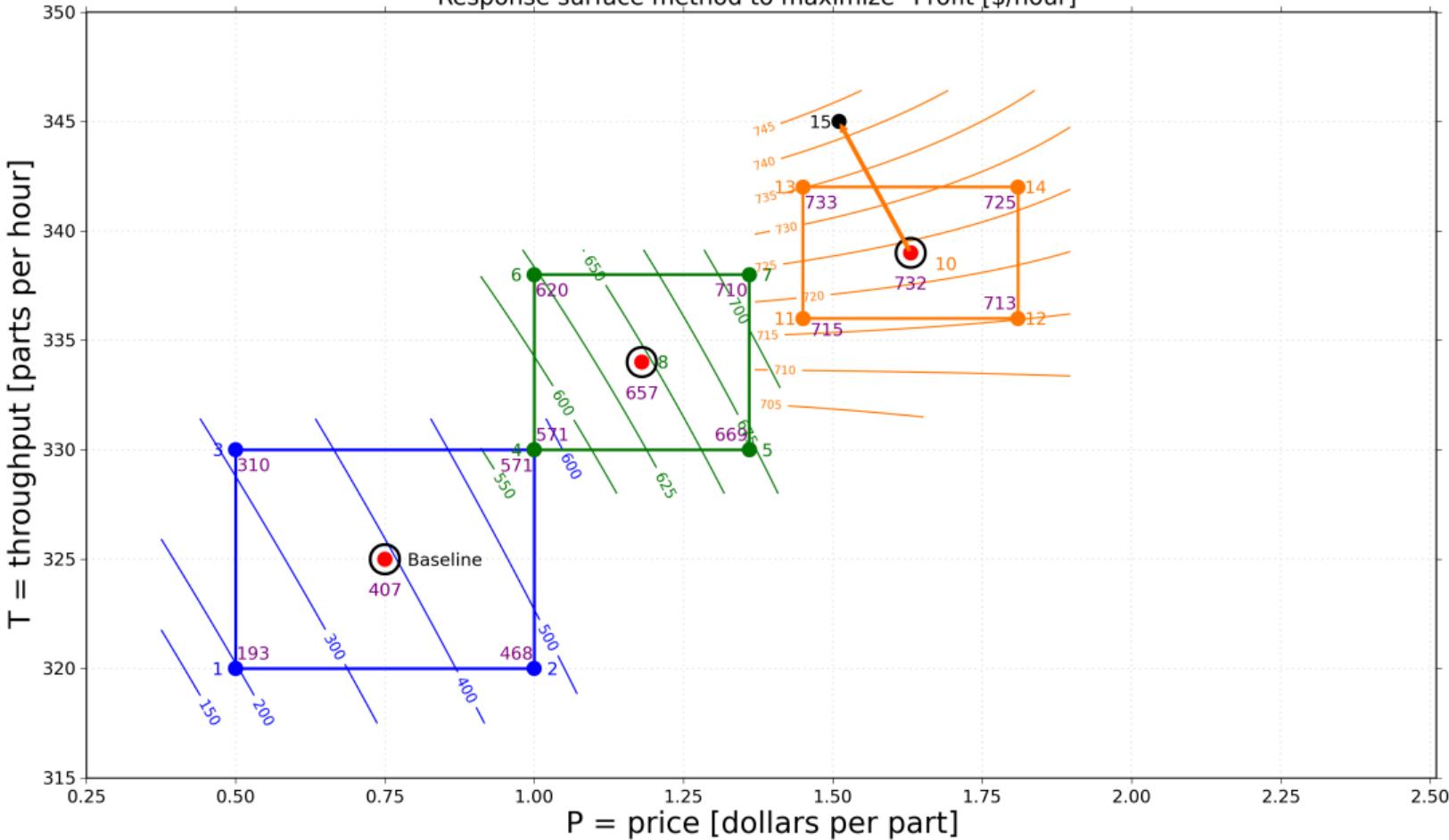
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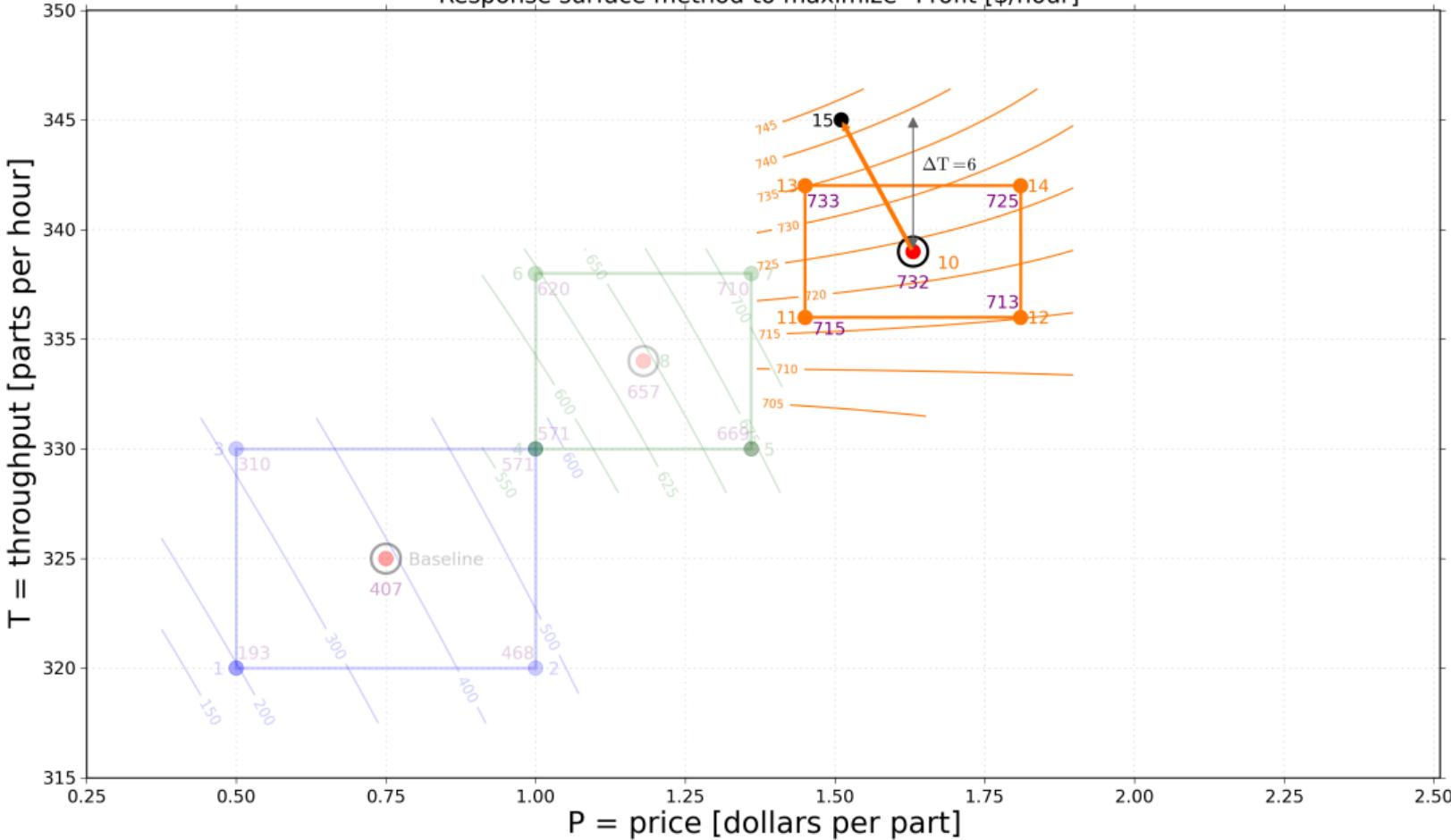


Response surface method to maximize "Profit [\$/hour]"

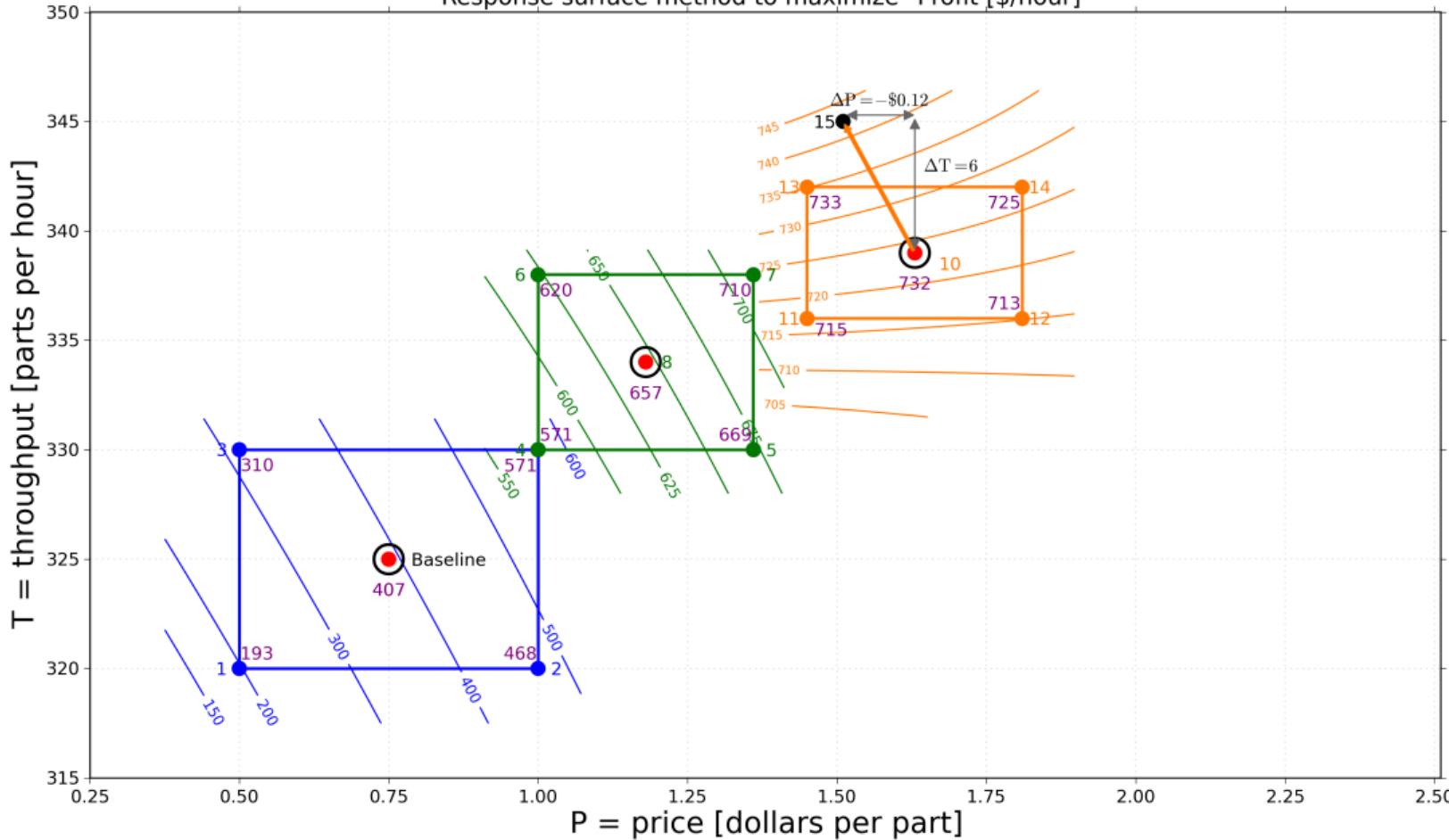


Response surface method to maximize "Profit [\$/hour]"

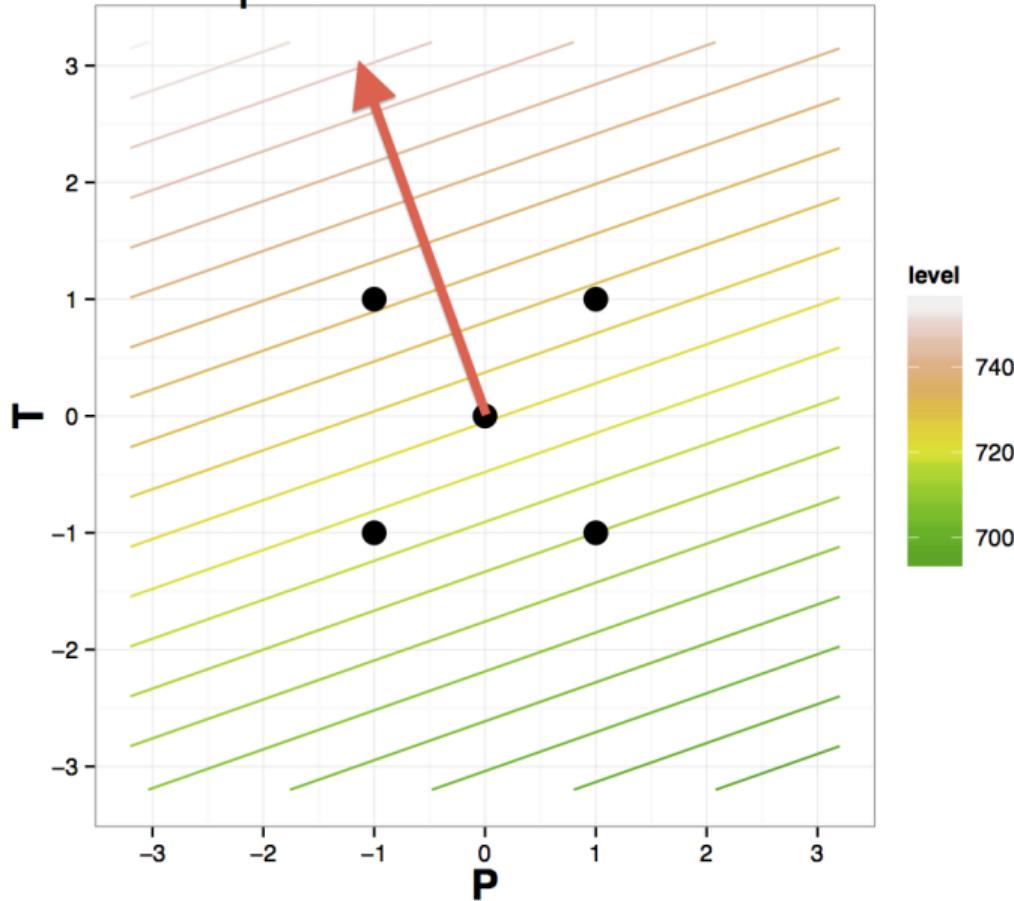
T = throughput [parts per hour]



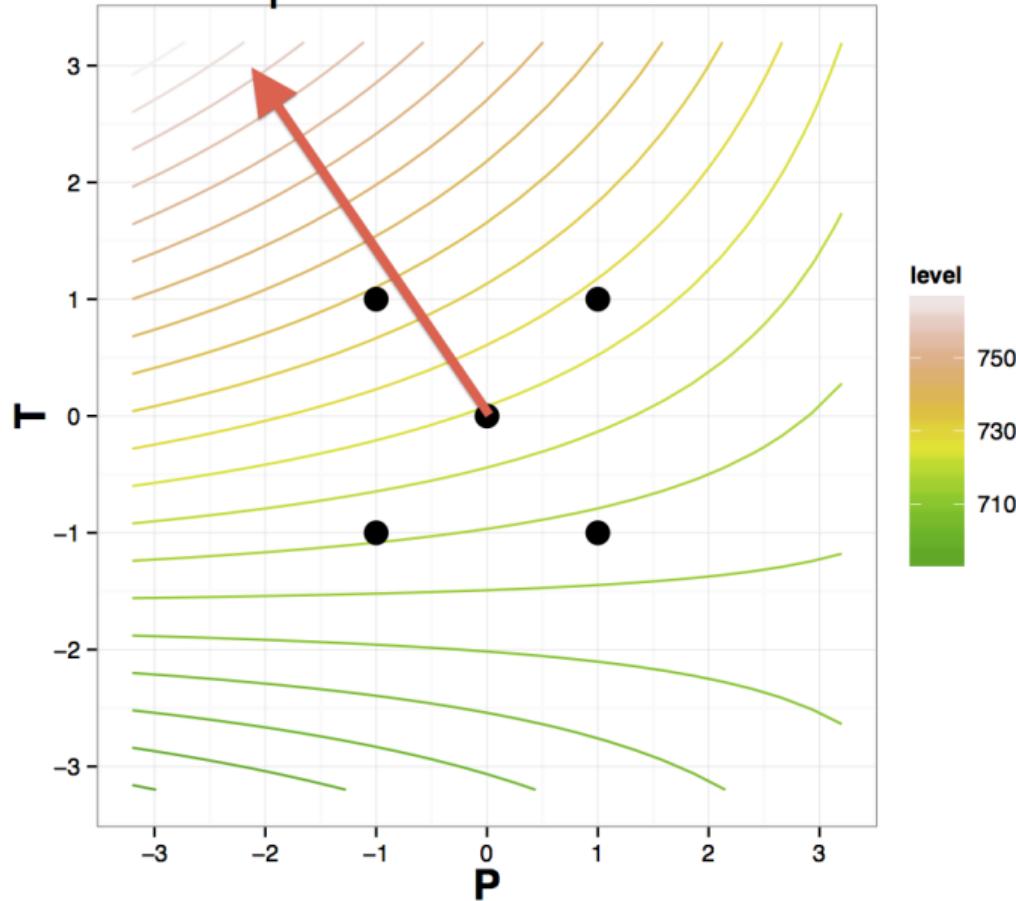
Response surface method to maximize "Profit [\$/hour]"



Contour plot with NO interaction term



Contour plot WITH interaction term



The 3 models we have built so far

Factorial 1:

$$\hat{y} = 389.8 + 134x_P + 55x_T - 3.5x_Px_T$$

Factorial 2:

$$\hat{y} = 645.4 + 47x_P + 22.500x_T - 2.0x_Px_T$$

Factorial 3:

$$\hat{y} = 723.6 - 2.5x_P + 7.500x_T - 1.5x_Px_T$$

Taking the next step for experiment 15: solution

- Pick change in coded units in one factor.
- Find the ratios for the other factor(s).
- Calculate step size in coded units.
- Convert these to real-world *changes*.
- Get the real-world location of the next experiment.
- Convert these back to coded-units.
- Predict the next experiment's outcome.
- Now run the next experiment, and record the values

Price

$$\Delta x_P = \frac{b_P}{b_T} \times \Delta x_T$$

$$\Delta x_P = \frac{-2.5}{7.5} \times 2 = -\frac{2}{3}$$

$$\Delta P = -\frac{2}{3} \cdot \frac{1}{2}(0.36) = -\$0.12$$

$$P^{(15)} = P^{(10)} + \Delta P = \$1.63 - 0.12 = \$1.51$$

$$x_P^{(15)} = \frac{1.51 - 1.63}{\frac{1}{2} \cdot (0.36)} = -\frac{2}{3}$$

Throughput

$$\Delta x_T = 2 \text{ (this was chosen)}$$

$$\Delta x_T = 2$$

$$\Delta T = 6$$

$$T^{(15)} = T^{(10)} + \Delta T$$

$$T^{(15)} = 339 + 6 = 345$$

$$x_T^{(15)} = 2$$

$$\hat{y} = 723.6 - 2.5x_P + 7.5x_T - 1.5x_P x_T$$

$$\hat{y}^{(15)} \approx \$742 \text{ profit per hour}$$

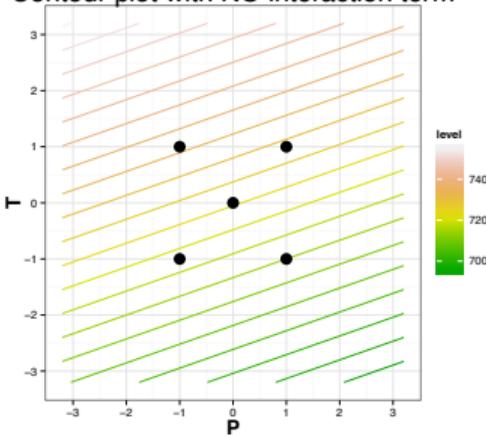
$$y^{(15)} = \$735 \text{ profit per hour}$$

Dealing with curvature when we suspect we are approaching an optimum

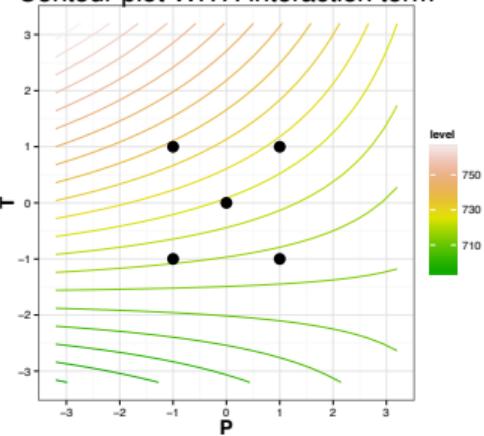
We detect curvature in several ways (in practice, you will detect one or more of these)

1. interaction terms are comparable to main effects

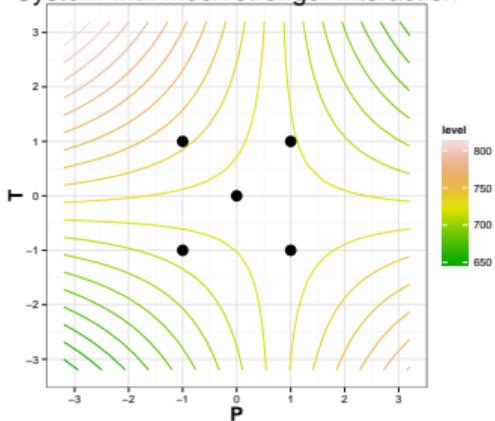
Contour plot with NO interaction term



Contour plot WITH interaction term



System with much stronger interaction



$$\hat{y} = -2.5x_P + 7.5x_T + 0 \cdot x_P x_T$$

$$\hat{y} = -2.5x_P + 7.5x_T - 1.5x_P x_T$$

$$\hat{y} = -2.5x_P + 5.35x_T - 7.5x_P x_T$$

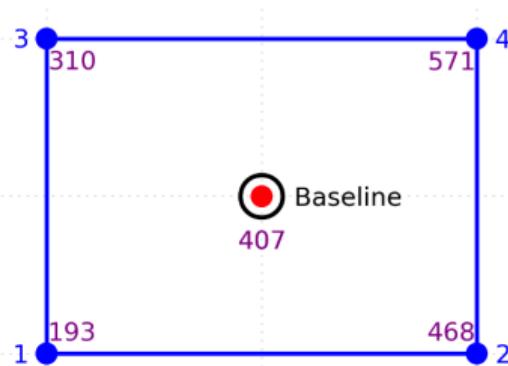
Dealing with curvature when we suspect we are approaching an optimum

We detect curvature in several ways (in practice, you will detect one or more of these)

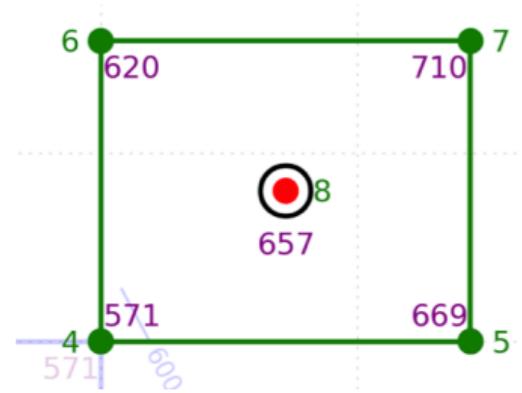
2. differences in the spread* are becoming smaller and smaller

*can be crudely quantified as (highest outcome) – (lowest outcome)

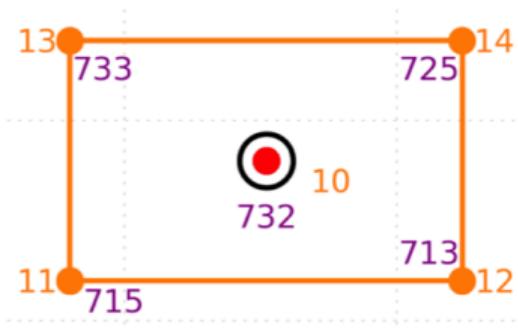
Factorial 1



Factorial 2



Factorial 3

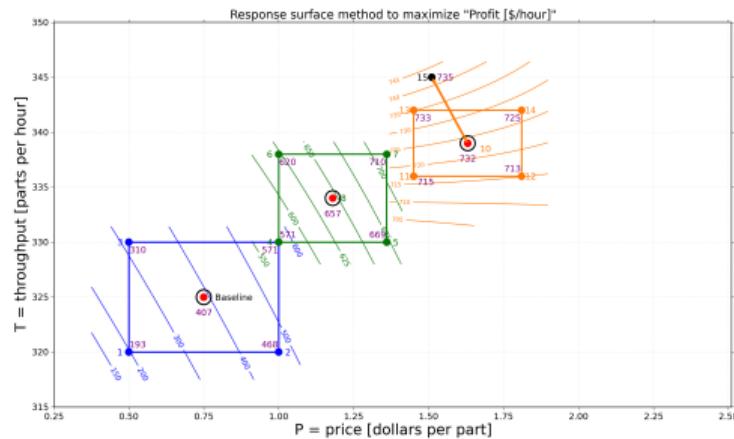


spread = \$ 378

spread = \$ 139

spread = \$ 20

Aside: If we are judging differences, we need an estimate of “noise”

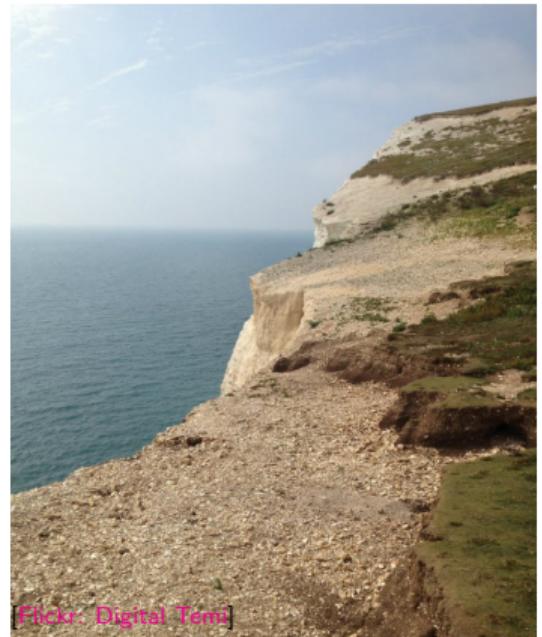


Dealing with curvature when we suspect we are approaching an optimum
We detect curvature in several ways (in practice, you will detect one or more of these)

3. we notice prediction errors with our model that indicate the surface is changing

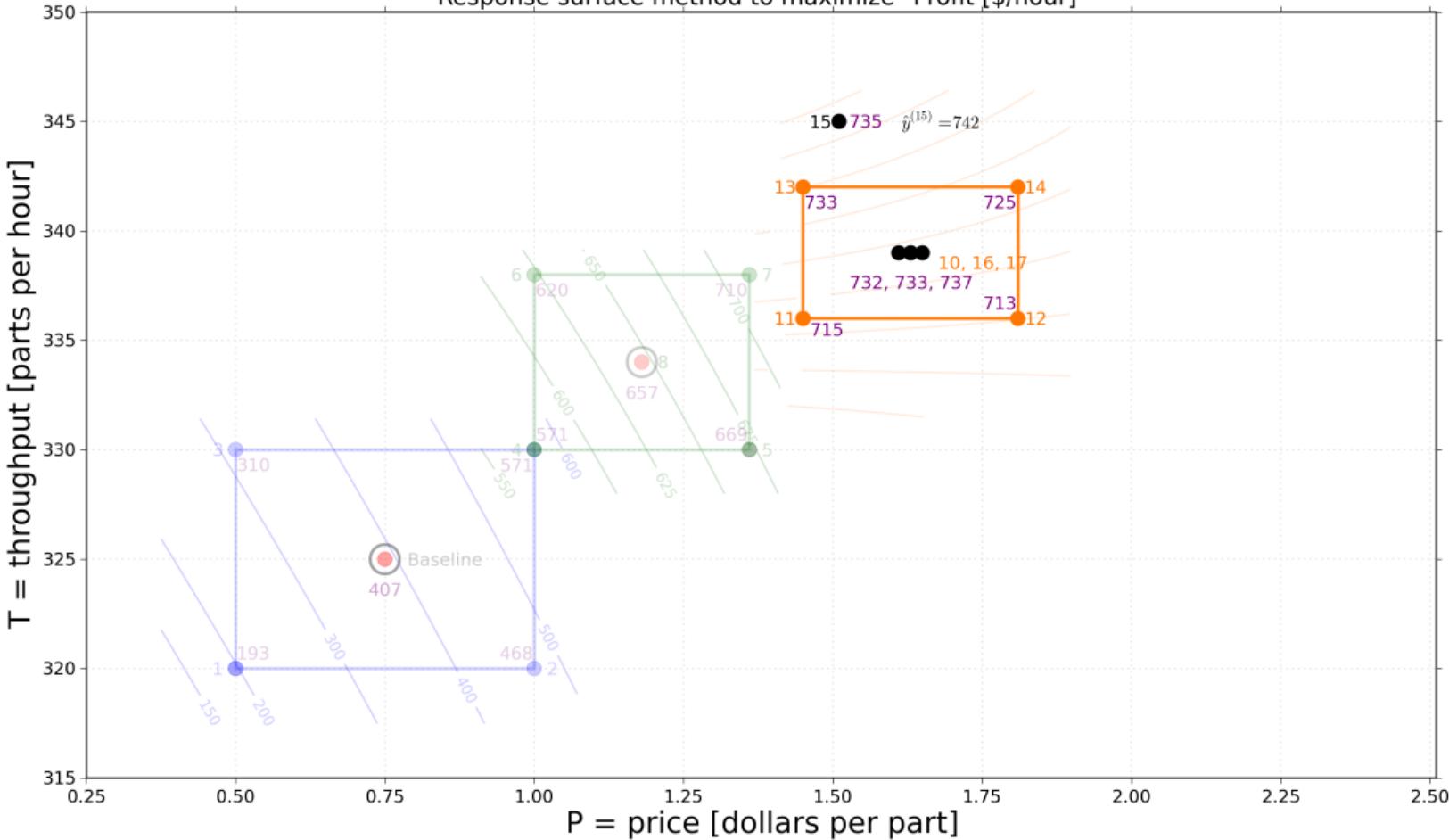


[Flickr: rmkoske]



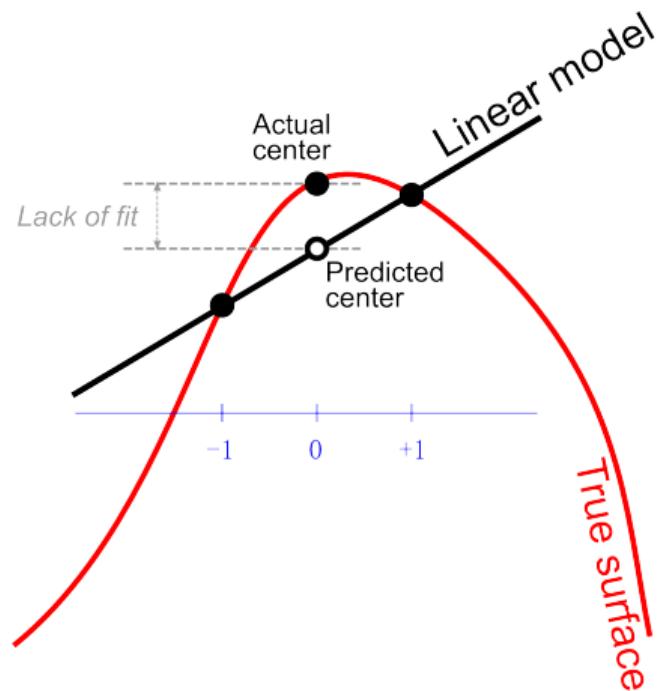
[Flickr: Digital_Term]

Response surface method to maximize "Profit [\$/hour]"



Dealing with curvature when we suspect we are approaching an optimum
We detect curvature in several ways (in practice, you will detect one or more of these)

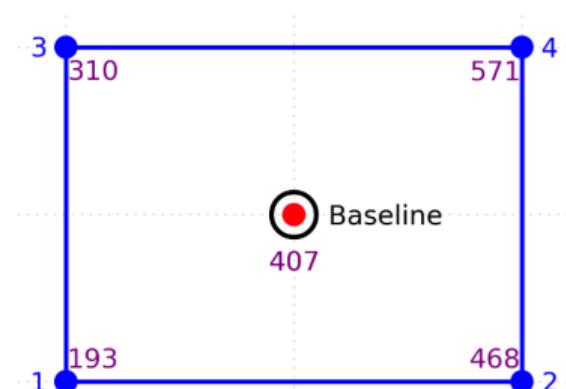
4. we detect “lack of fit” in our empirical model



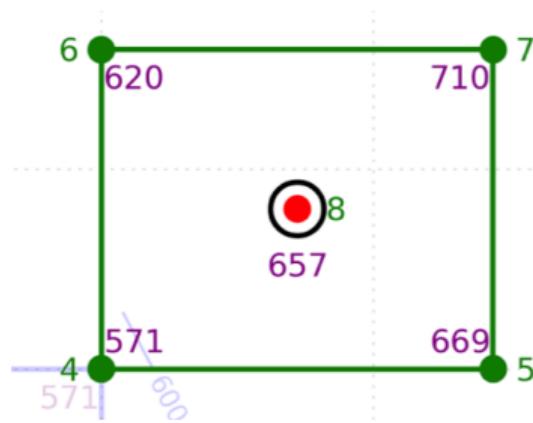
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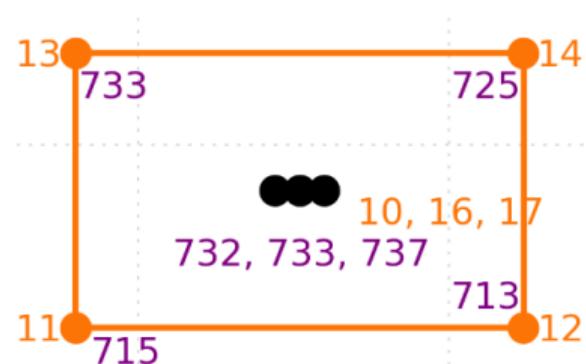
4. we detect “lack of fit” in our empirical model



$$\hat{y} = 390 + 134x_P + 55x_T - 3.5x_Px_T$$
$$\begin{aligned} y^{(0)} &= \$407 \\ \hat{y}^{(0)} &= \$390 \end{aligned} \quad \left. \right\} \text{difference} = \$17$$



$$\hat{y} = 645 + 47x_P + 22.5x_T - 2.0x_Px_T$$
$$\begin{aligned} y^{(8)} &= \$657 \\ \hat{y}^{(8)} &= \$645 \end{aligned} \quad \left. \right\} \text{difference} = \$12$$

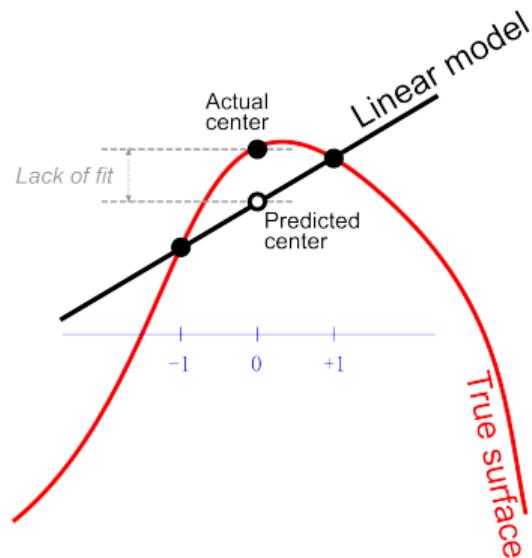
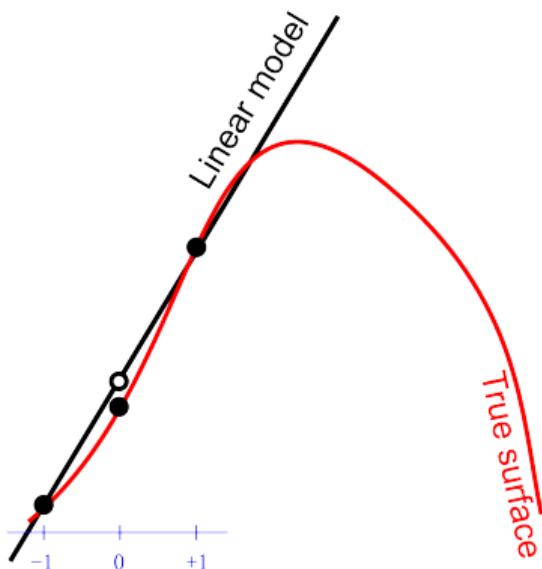


$$\hat{y} = 724 - 2.5x_P + 7.5x_T - 1.5x_Px_T$$
$$\begin{aligned} y^{(\text{mid})} &= \$734 \\ \hat{y}^{(\text{mid})} &= \$724 \end{aligned} \quad \left. \right\} \text{difference} = \$10$$

The one-dimensional equivalent of what we are seeing in two dimensions

We detect curvature in several ways (in practice, you will detect one or more of these)

4. we detect “lack of fit” in our empirical model



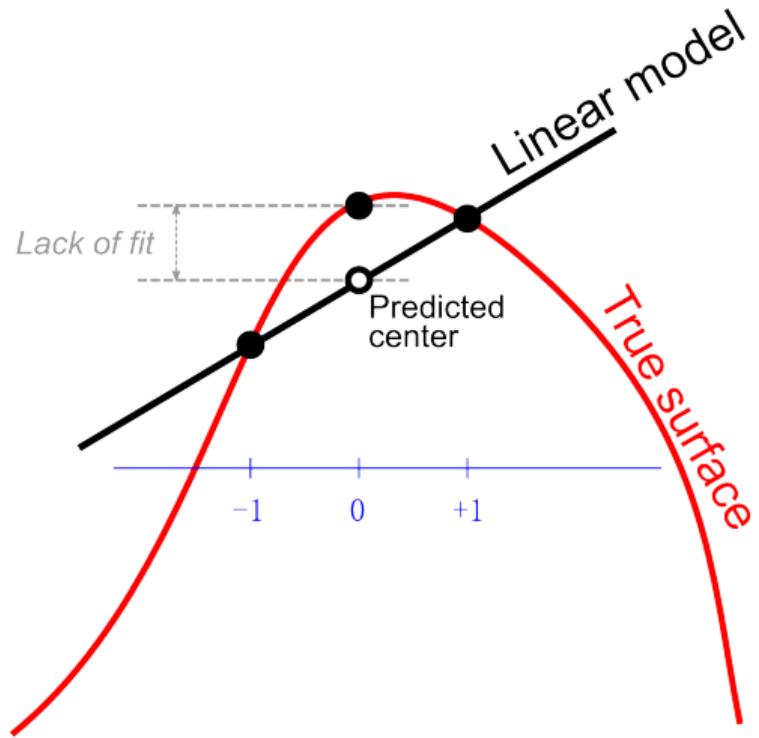
Dealing with curvature when we suspect we are approaching an optimum

We detect curvature in several ways (in practice, you will detect one or more of these)

1. interaction terms are comparable to main effects
2. differences in the spread are becoming smaller and smaller
3. we notice prediction errors with our model that indicate the surface is changing
4. we detect “lack of fit”
5. confidence intervals show some model coefficients are not significant

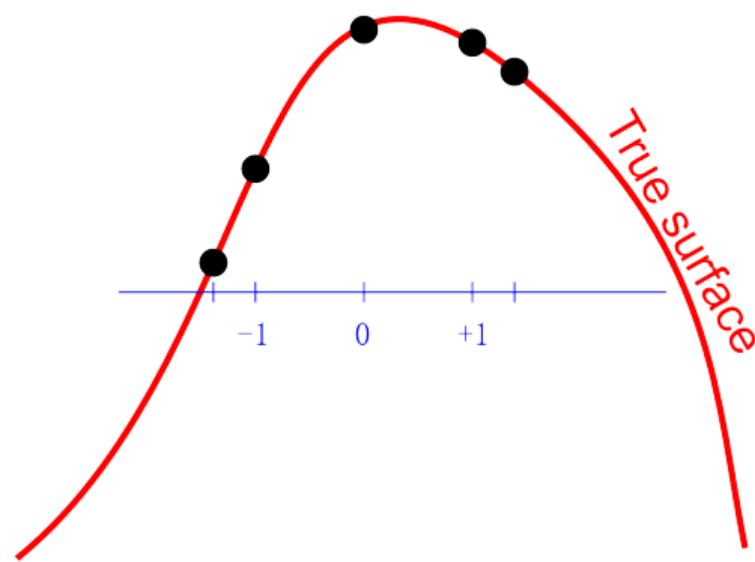
Improving the model's prediction ability by adding quadratic terms

Current situation, displaying lack of fit:



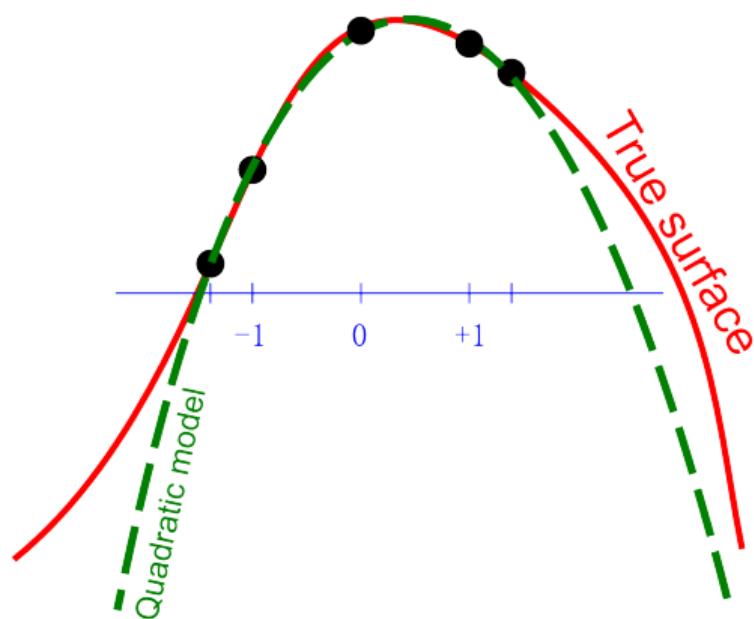
Improving the model's prediction ability by adding quadratic terms

Add specially placed points:

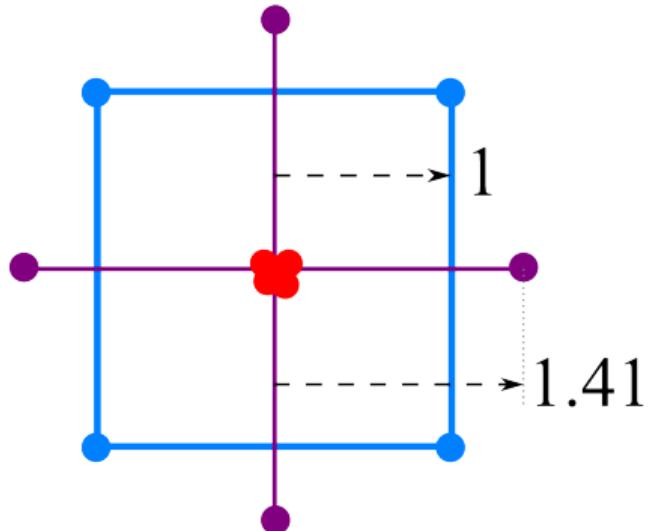
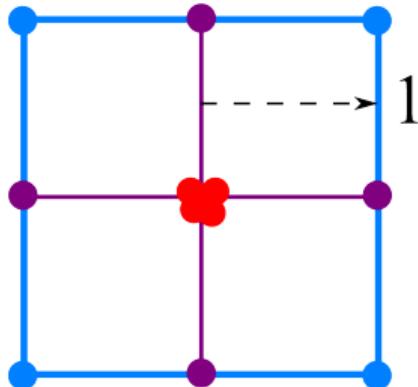


Improving the model's prediction ability by adding quadratic terms

And fit a quadratic model now:

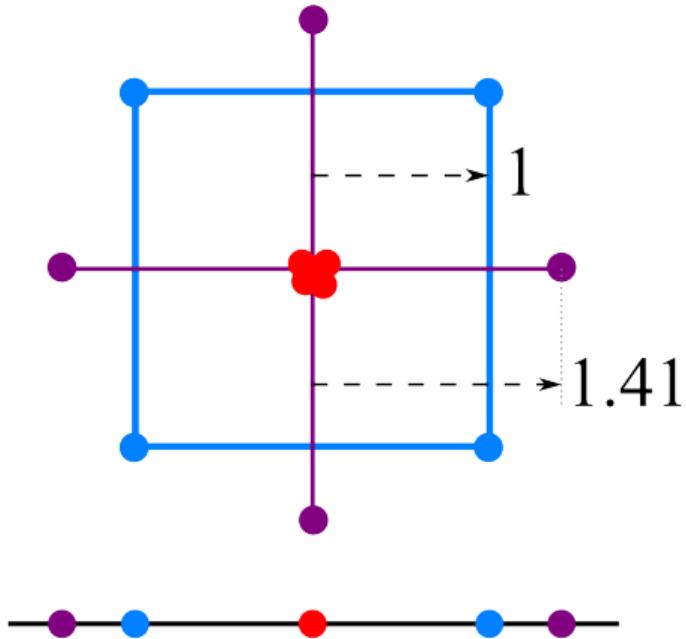
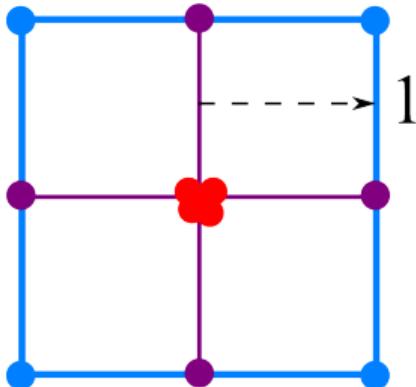


Adding experiments so we can fit quadratic terms: where do we put them?



$$\alpha = 1.41$$

Adding experiments so we can fit quadratic terms: where do we put them?



$$\alpha = 1.41$$

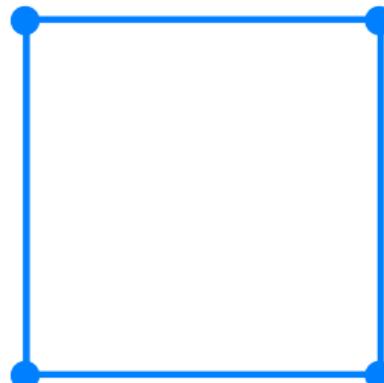
Adding experiments so we can fit quadratic terms: where do we put them?

- ▶ Run the factorial points first
- ▶ Then run the star (axial) points after*

$$\alpha = (2^k)^{0.25}$$

- ▶ $k = 2$; then $\alpha = \sqrt{2} \approx 1.41$
- ▶ $k = 3$; then $\alpha = 2^{\frac{3}{4}} \approx 1.68$

- ▶ Run several center points randomly, during the above two stages



* Astute viewers will wonder about confounding disturbances, since these runs are not randomized.

You can show that these **two groups** of experiments are blocked.

$$\alpha = 1.41$$

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- ▶ Run the factorial points first
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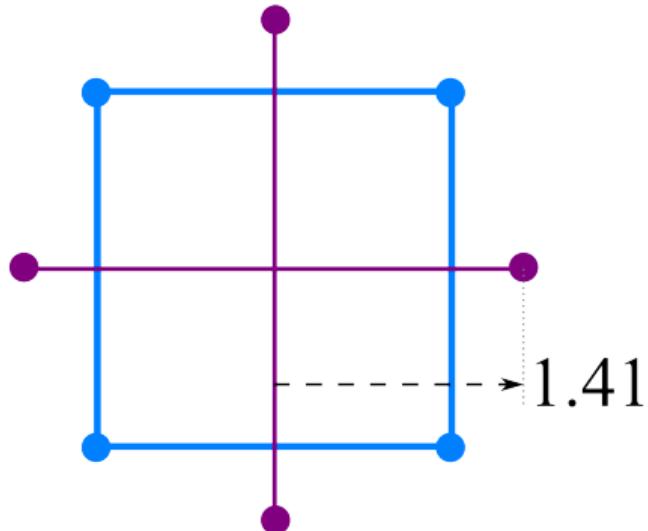
$$\alpha = (2^k)^{0.25}$$

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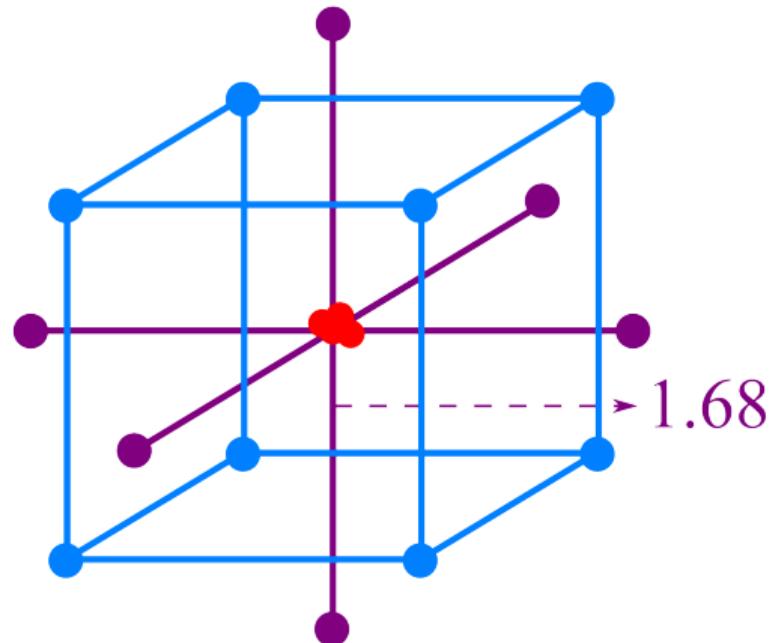
$$\alpha = (2^k)^{0.25}$$

- ▶ $k = 2$; then $\alpha = \sqrt{2} \approx 1.41$
- ▶ $k = 3$; then $\alpha = 2^{3/4} \approx 1.68$

- ▶ Run several center points randomly, during the above two stages

* Astute viewers will wonder about confounding disturbances, since these runs are not randomized.

You can show that these **two groups** of experiments are blocked.



$$\alpha = 1.68$$

Adding experiments so we can fit quadratic terms: where do we put them?

- ▶ Run the factorial points first
- ▶ Then run the star (axial) points after*

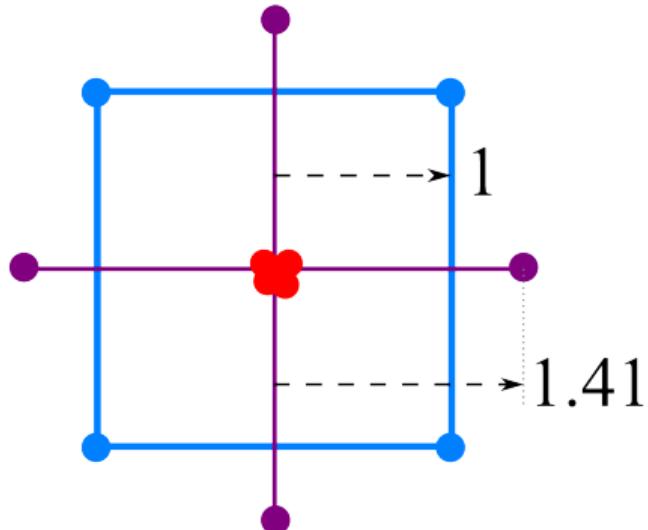
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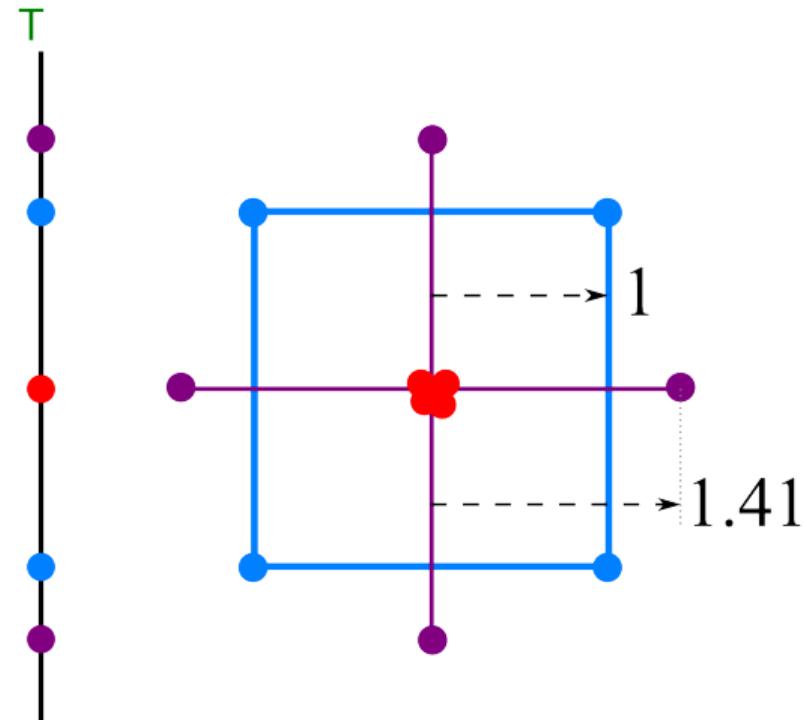
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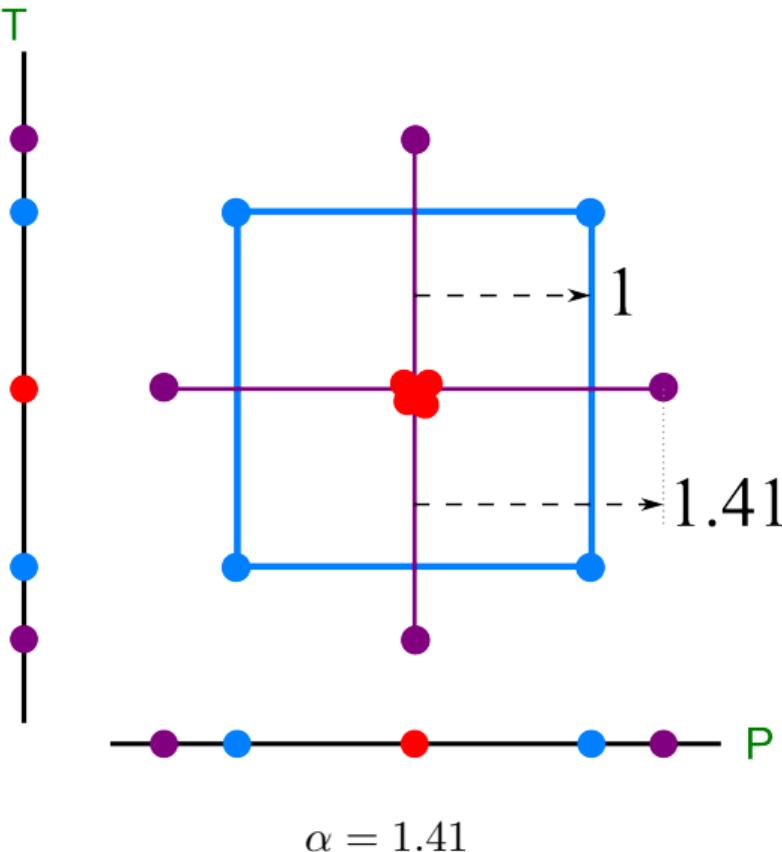
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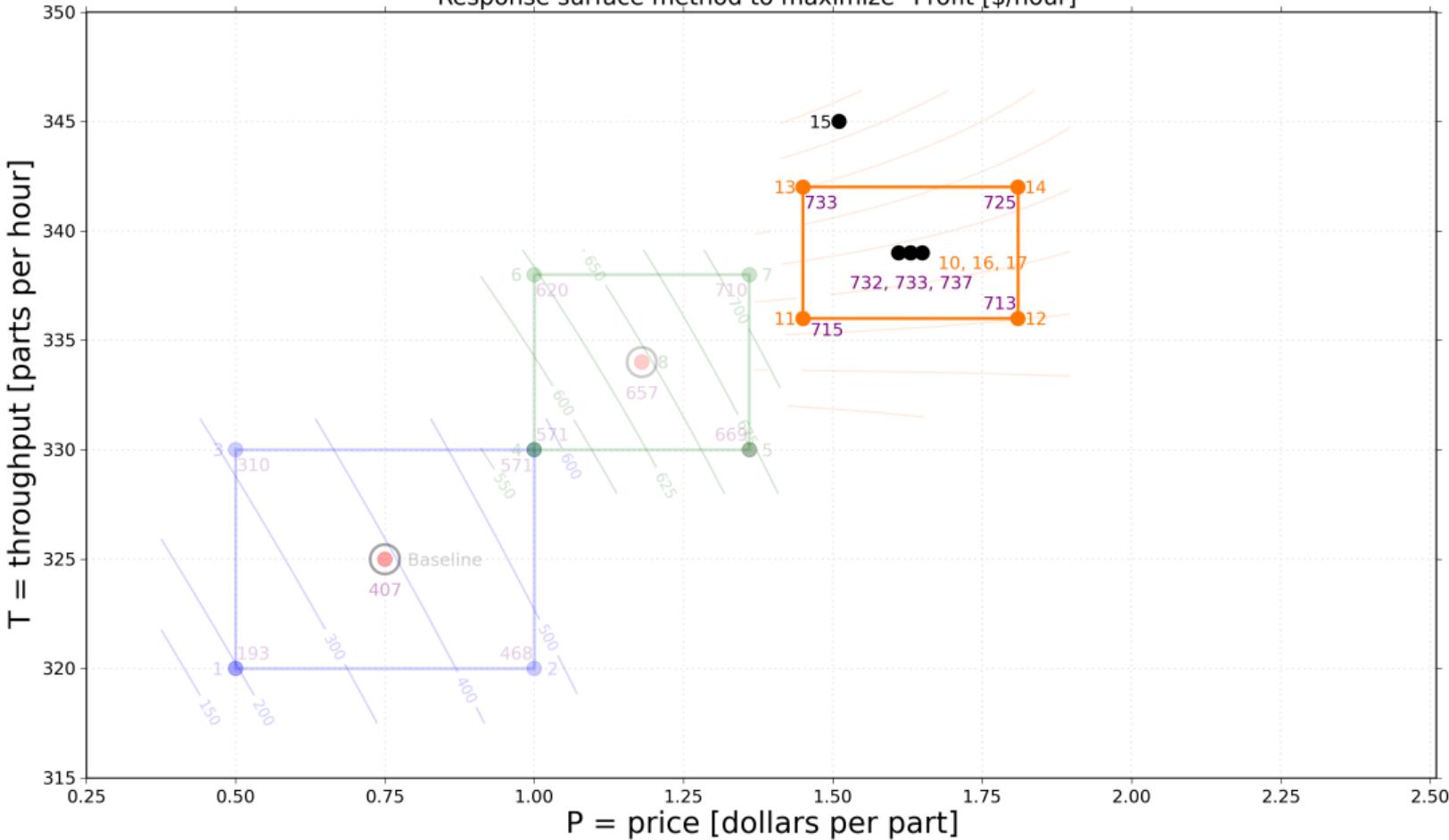
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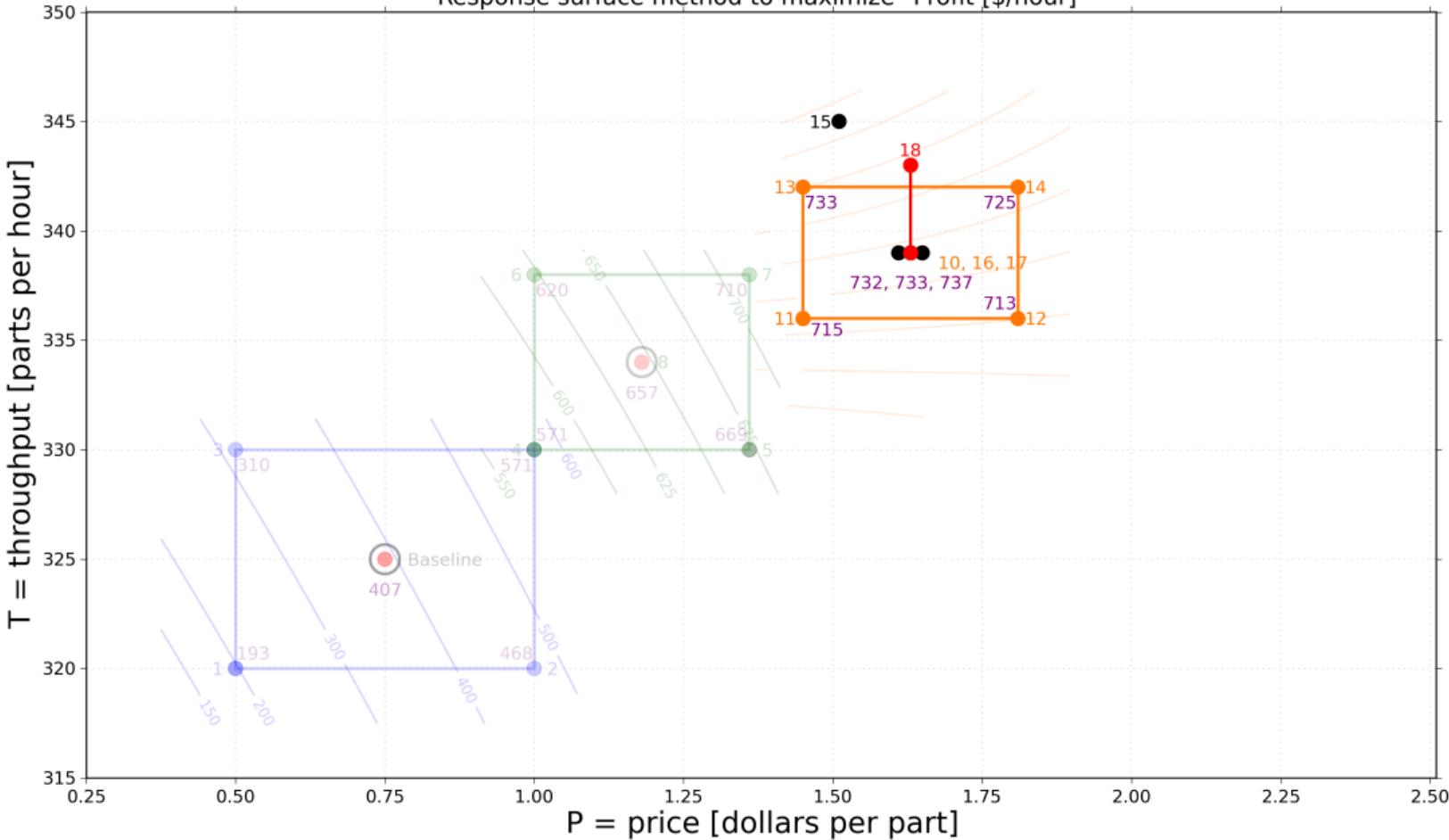
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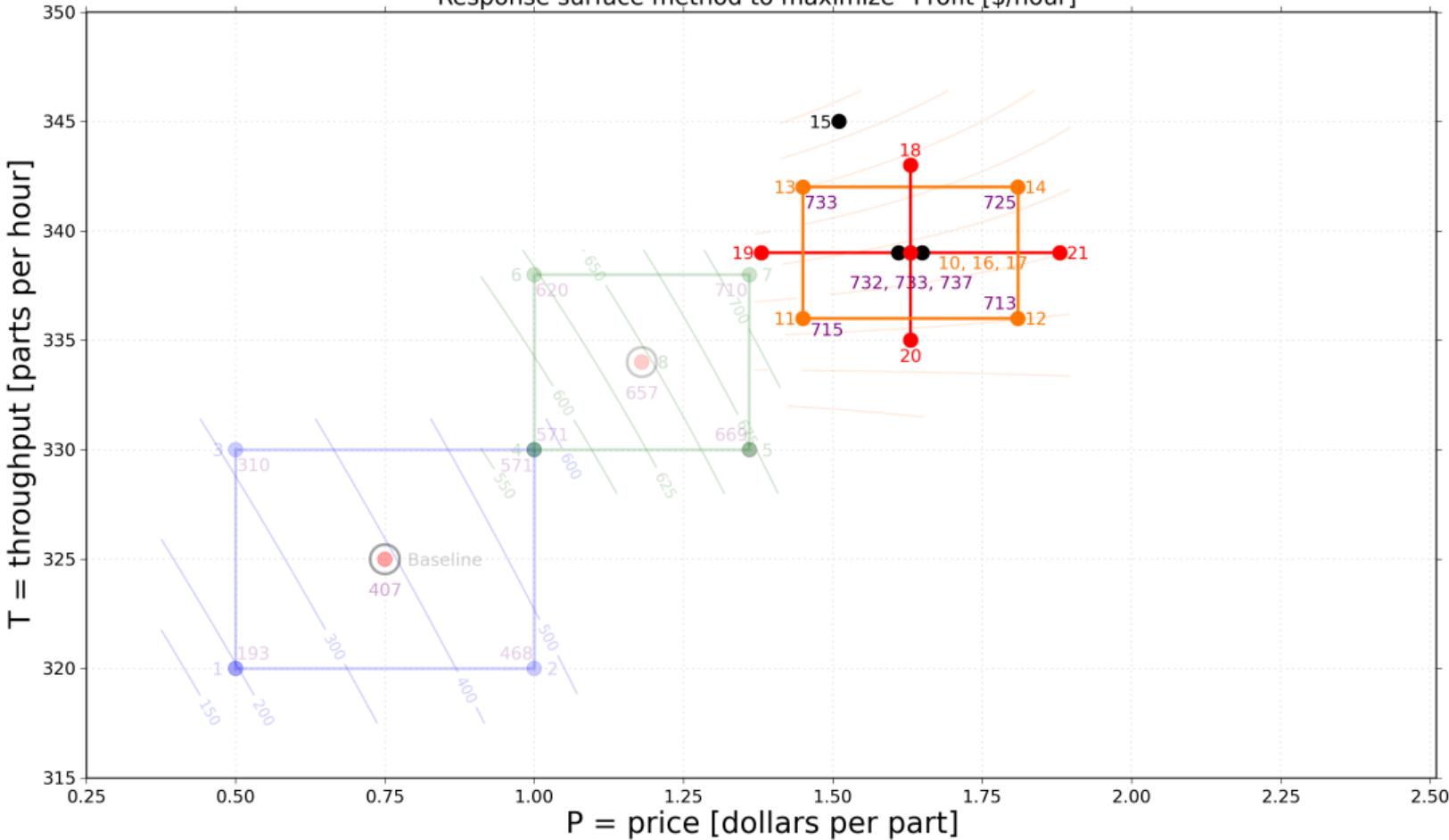
Response surface method to maximize "Profit [\$/hour]"



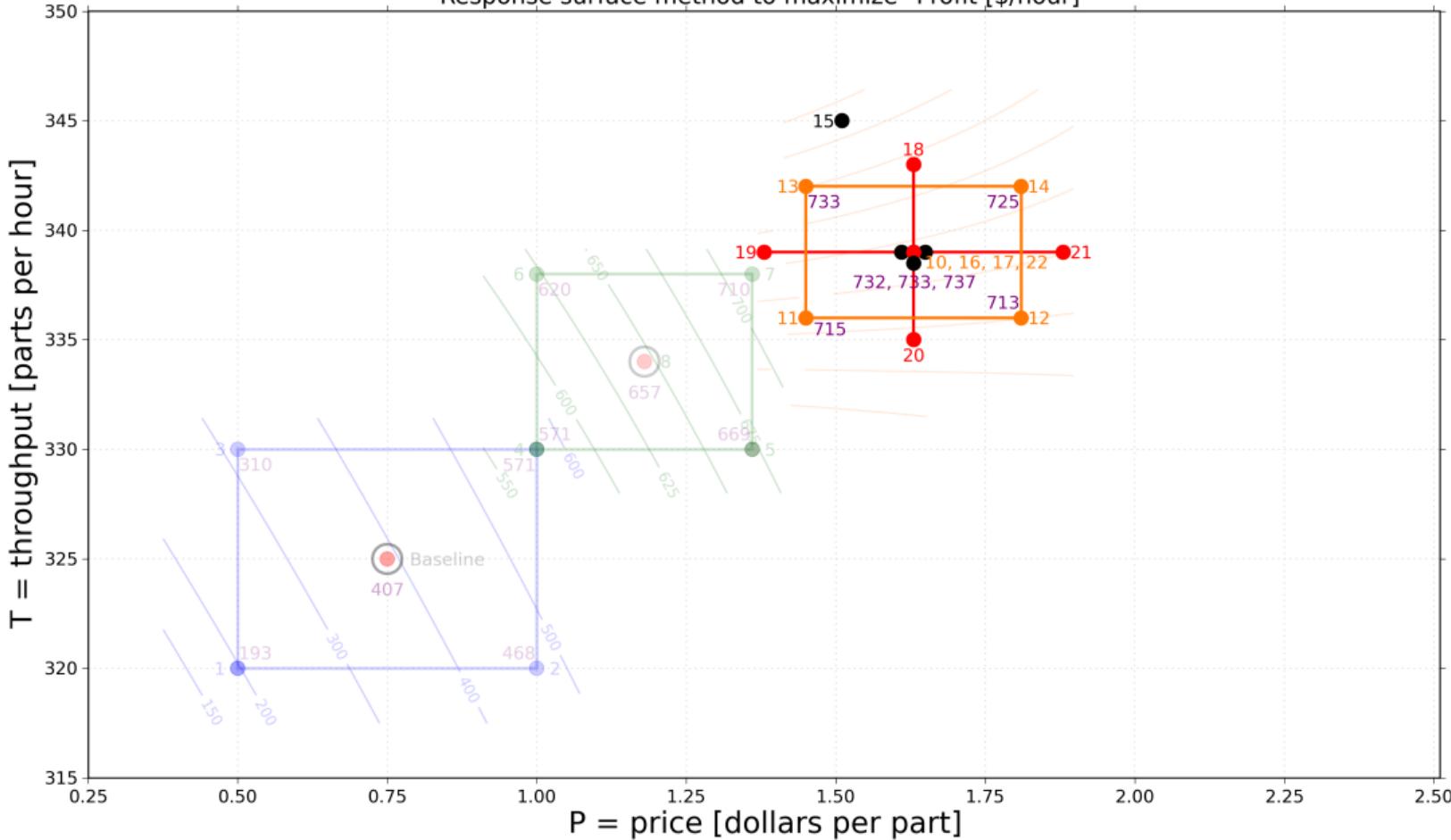
Response surface method to maximize "Profit [\$/hour]"



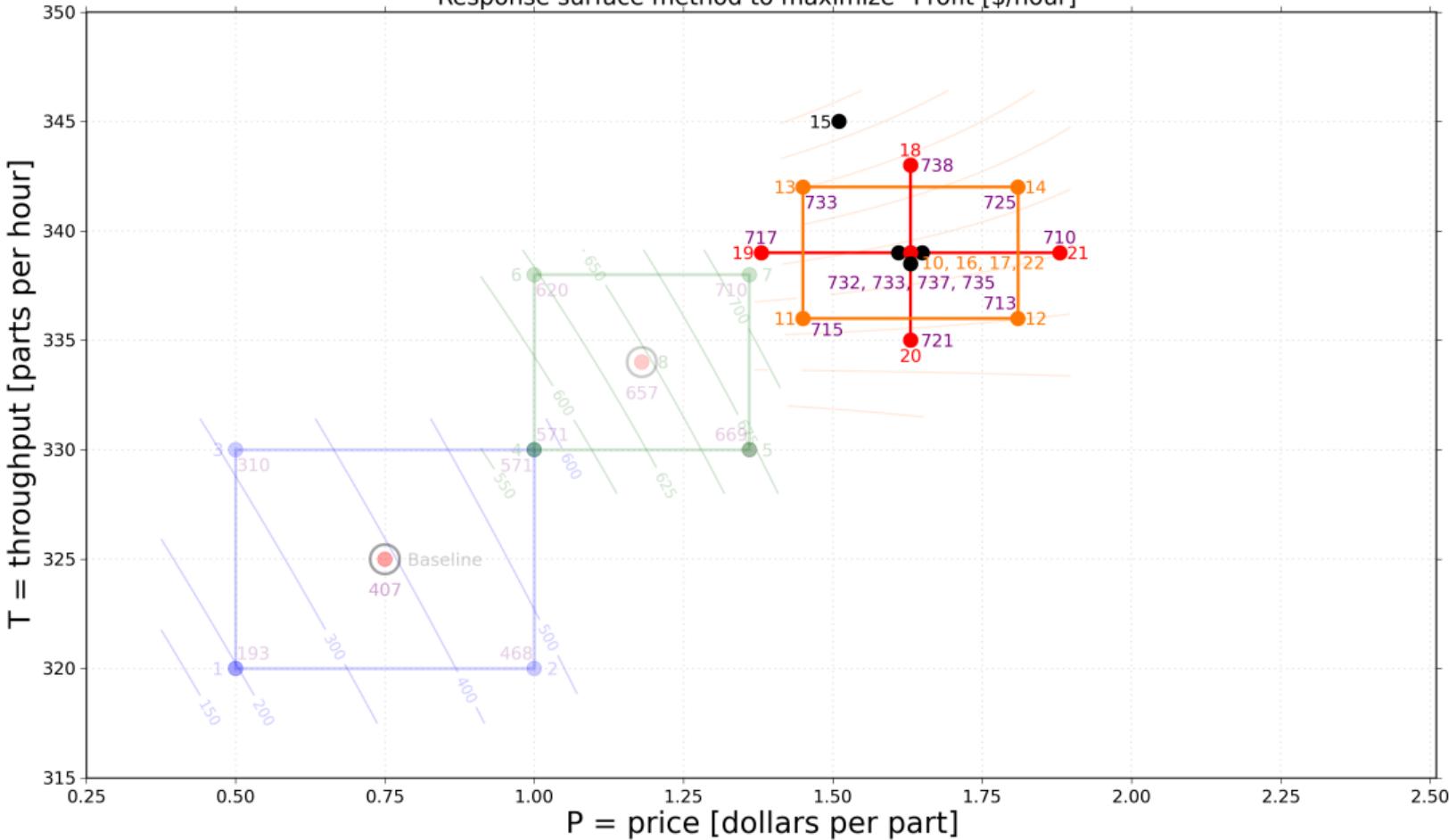
Response surface method to maximize "Profit [\$/hour]"



Response surface method to maximize "Profit [\$/hour]"



Response surface method to maximize "Profit [\$/hour]"



List of all experiments

Results of the 12 runs: (factorial + star + center). Are we nearly there?

$$\hat{y} = 734.23 - 2.5x_P + 6.97x_T - 10.6x_P^2 - 2.5x_T^2 - 1.5x_P x_T$$

1. We get good predictions at the center, indicating a “small lack of fit”

- ▶ $\hat{y}^{(\text{center})} = \734
- ▶ $y_{\text{actual}}^{(\text{center})} = \734.25

2. We have good predictions of other points in the region

```
# Predict value of point 15 (actual value was $735)
predict(model.7, data.frame(P=-2/3, T=2))
```

- ▶ $\hat{y}^{(15)} = \$737$
- ▶ $y_{\text{actual}}^{(15)} = \735

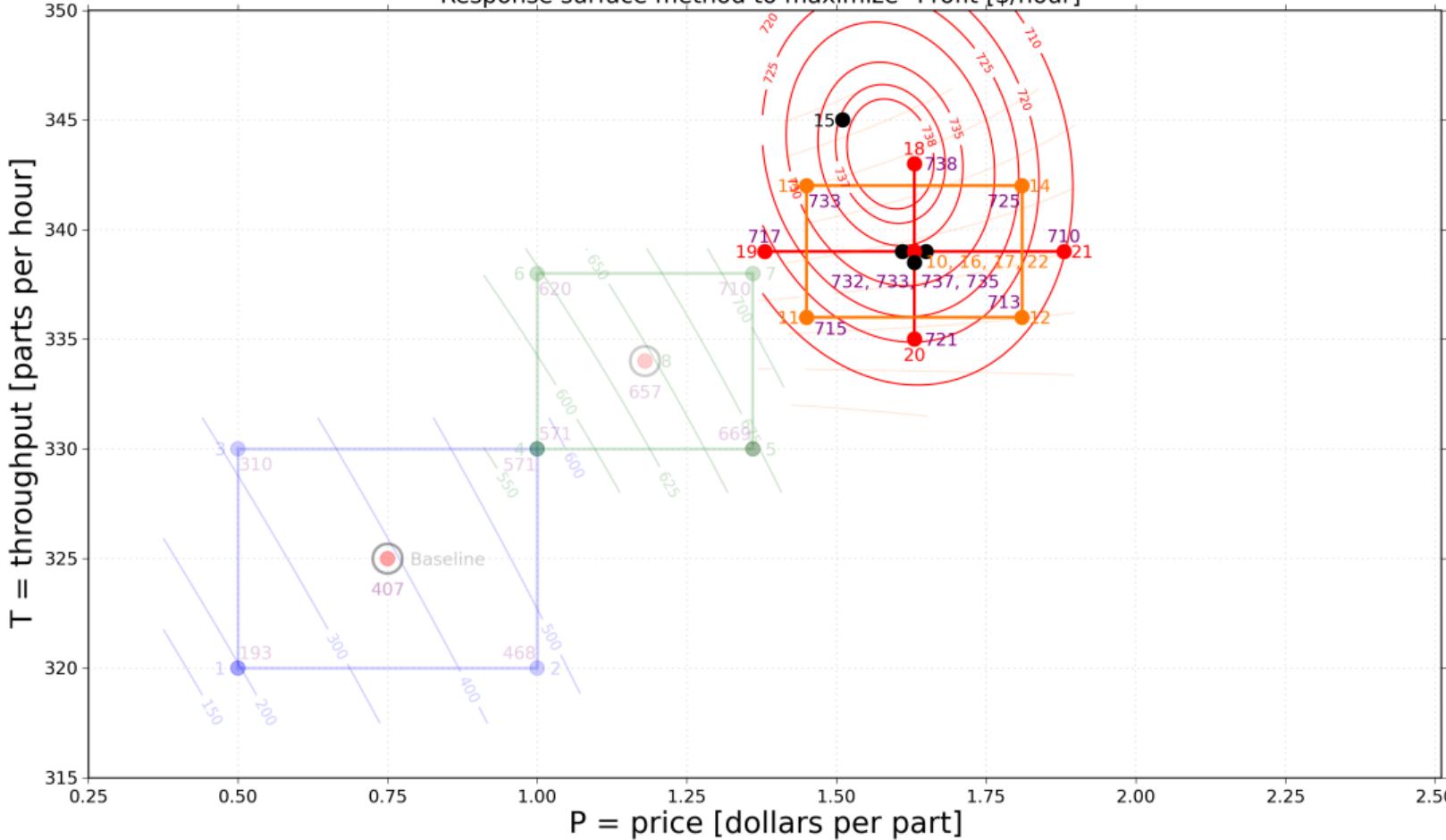
Output from the R software:

```
Residuals:
    Min      1Q  Median      3Q     Max 
-2.2248 -0.5393 -0.2176  0.7893  2.7752 

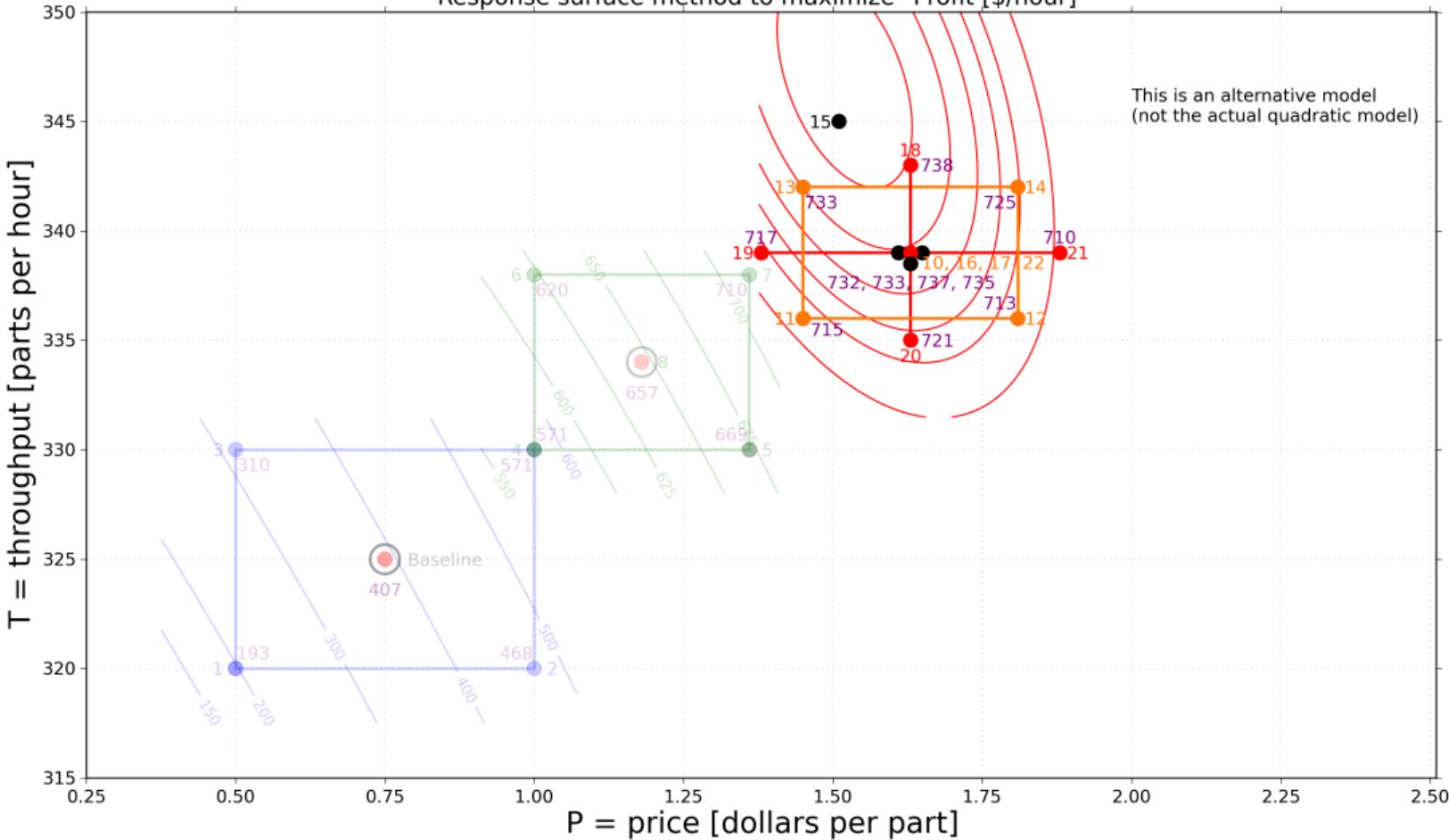
Coefficients:
            Estimate Std. Error t value Pr(>|t|)    
(Intercept) 734.2248   0.8642  849.571 < 2e-16 ***
P          -2.5098   0.6175  -4.064  0.00662 **  
T           6.9706   0.6298  11.069 3.24e-05 ***
I(P^2)      -10.5762  0.6989 -15.133 5.25e-06 ***
I(T^2)      -2.4604   0.7435  -3.309  0.01622 *  
P:T        -1.5000   0.8655  -1.733  0.13379    
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 1.731 on 6 degrees of freedom
Multiple R-squared:  0.9841,    Adjusted R-squared:  0.9709 
F-statistic: 74.37 on 5 and 6 DF,  p-value: 2.581e-05
```

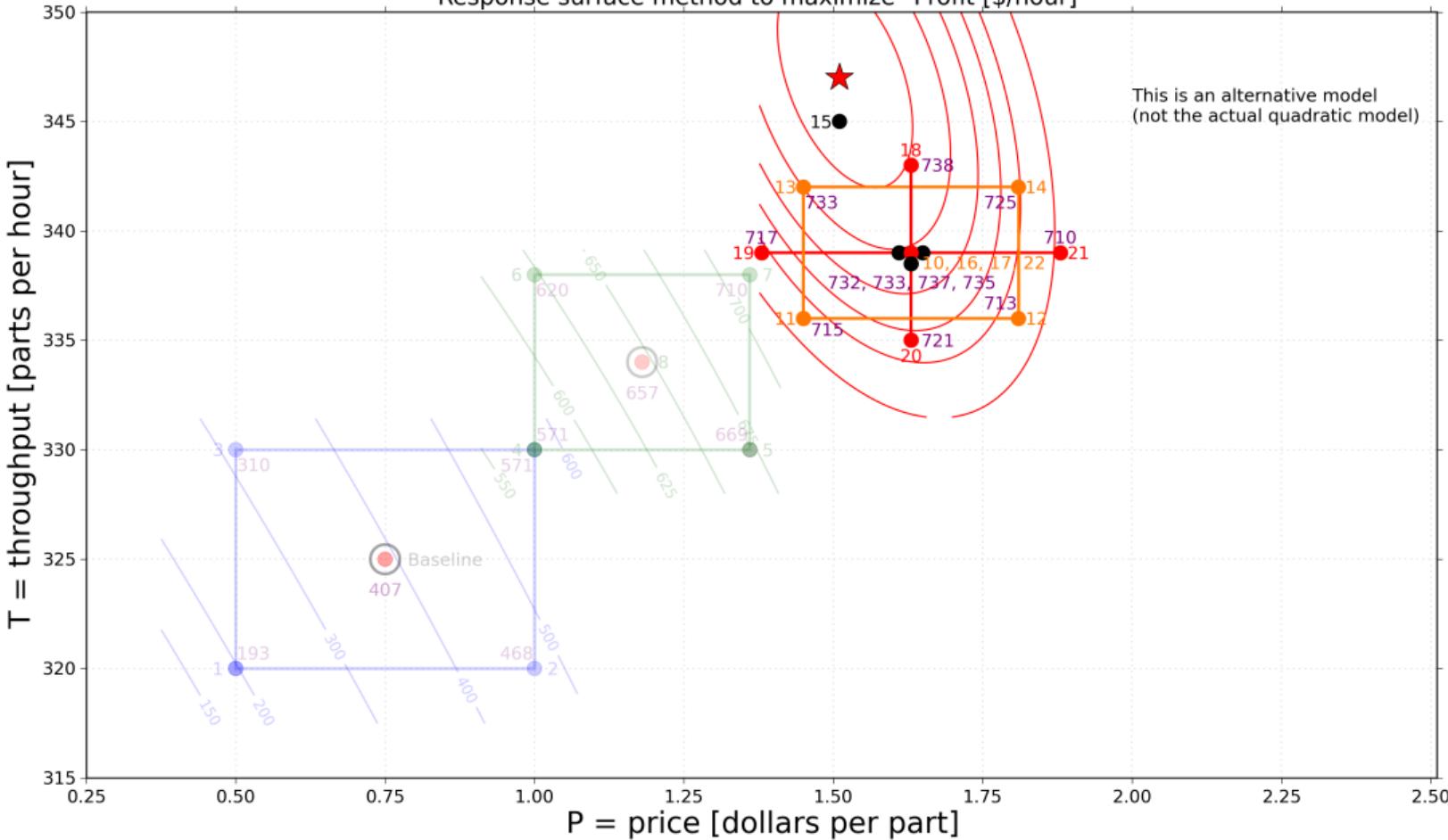
Response surface method to maximize "Profit [\$/hour]"



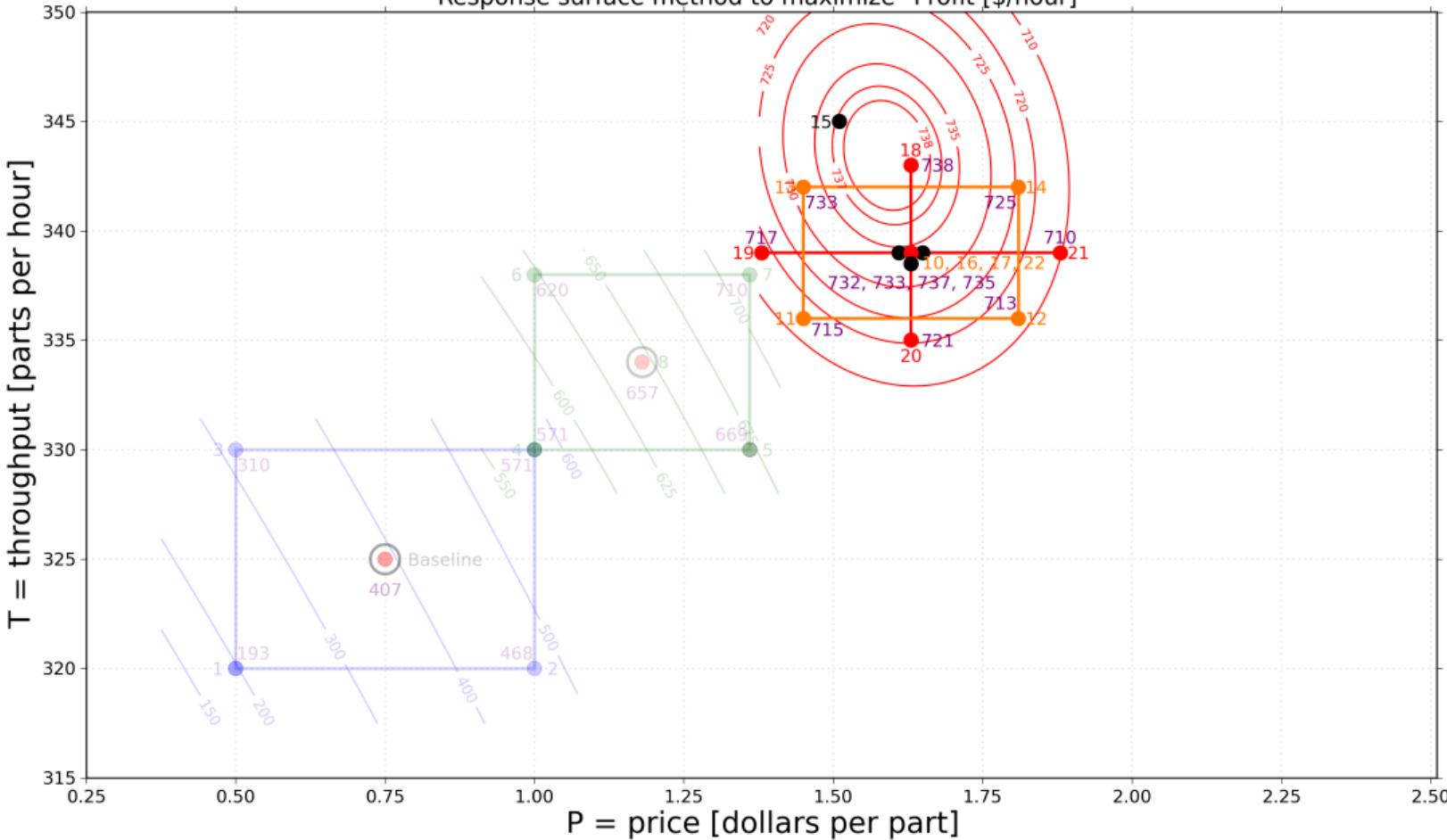
Response surface method to maximize "Profit [\$/hour]"



Response surface method to maximize "Profit [\$/hour]"



Response surface method to maximize "Profit [\$/hour]"



Finding the optimum analytically (with differentiation)

$$\hat{y} = 734 - 2.5x_P + 6.97x_T - 10.6x_P^2 - 2.5x_T^2 - 1.5x_Px_T$$

$$\frac{\partial \hat{y}}{\partial x_P} = -2.5 - 21.2x_P - 1.5x_T = 0$$

$$\frac{\partial \hat{y}}{\partial x_T} = 6.97 - 1.5x_P - 5.0x_T = 0$$

$$\begin{pmatrix} -21.2 & -1.5 \\ -1.5 & -5.0 \end{pmatrix} \begin{pmatrix} x_P \\ x_T \end{pmatrix} = \begin{pmatrix} 2.5 \\ -6.97 \end{pmatrix}$$

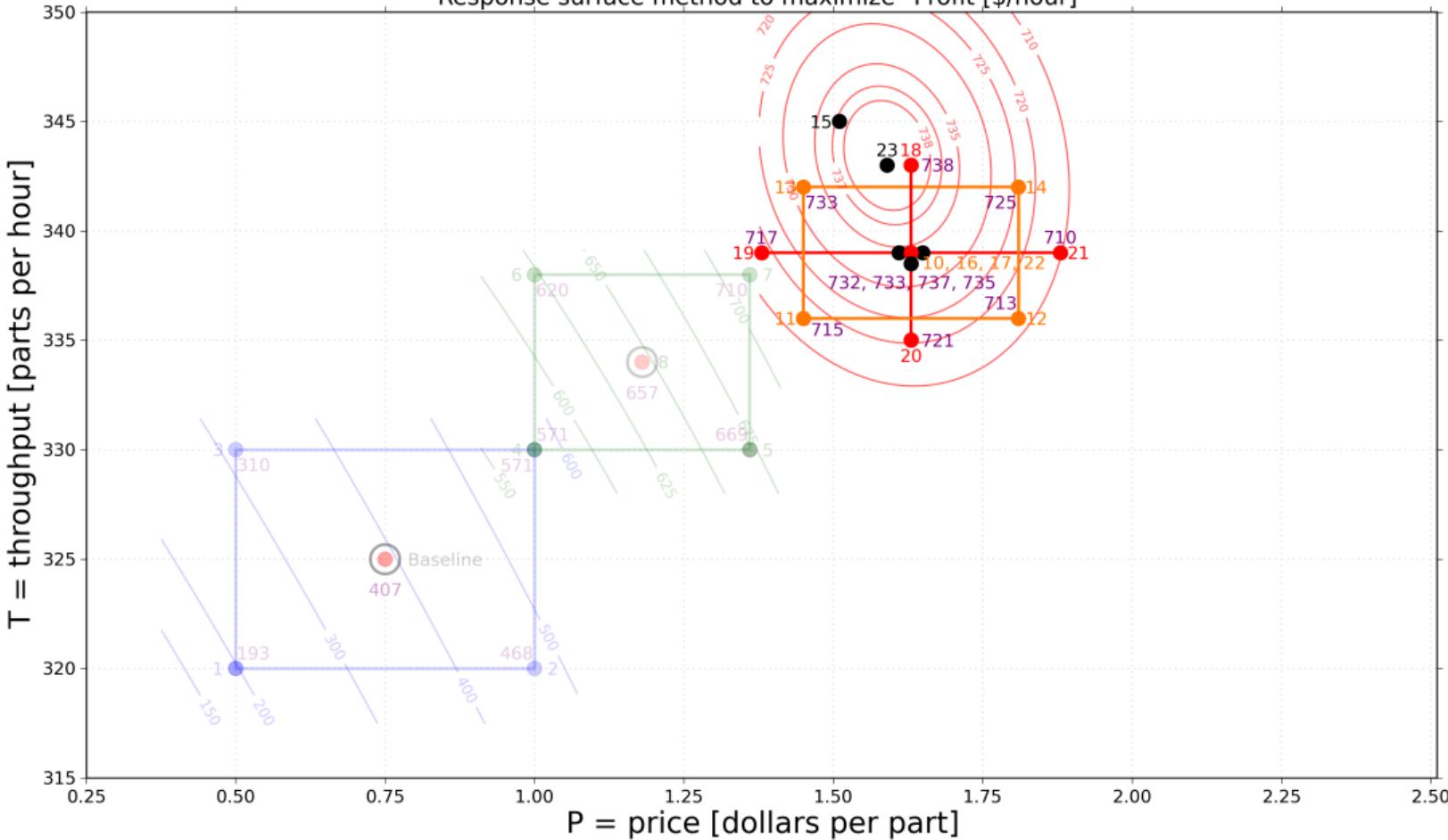
$$x_P^{(23)} = -0.22$$

$$P^{(23)} = -0.22 \cdot \frac{1}{2}(0.36) + 1.63 = \$1.59$$

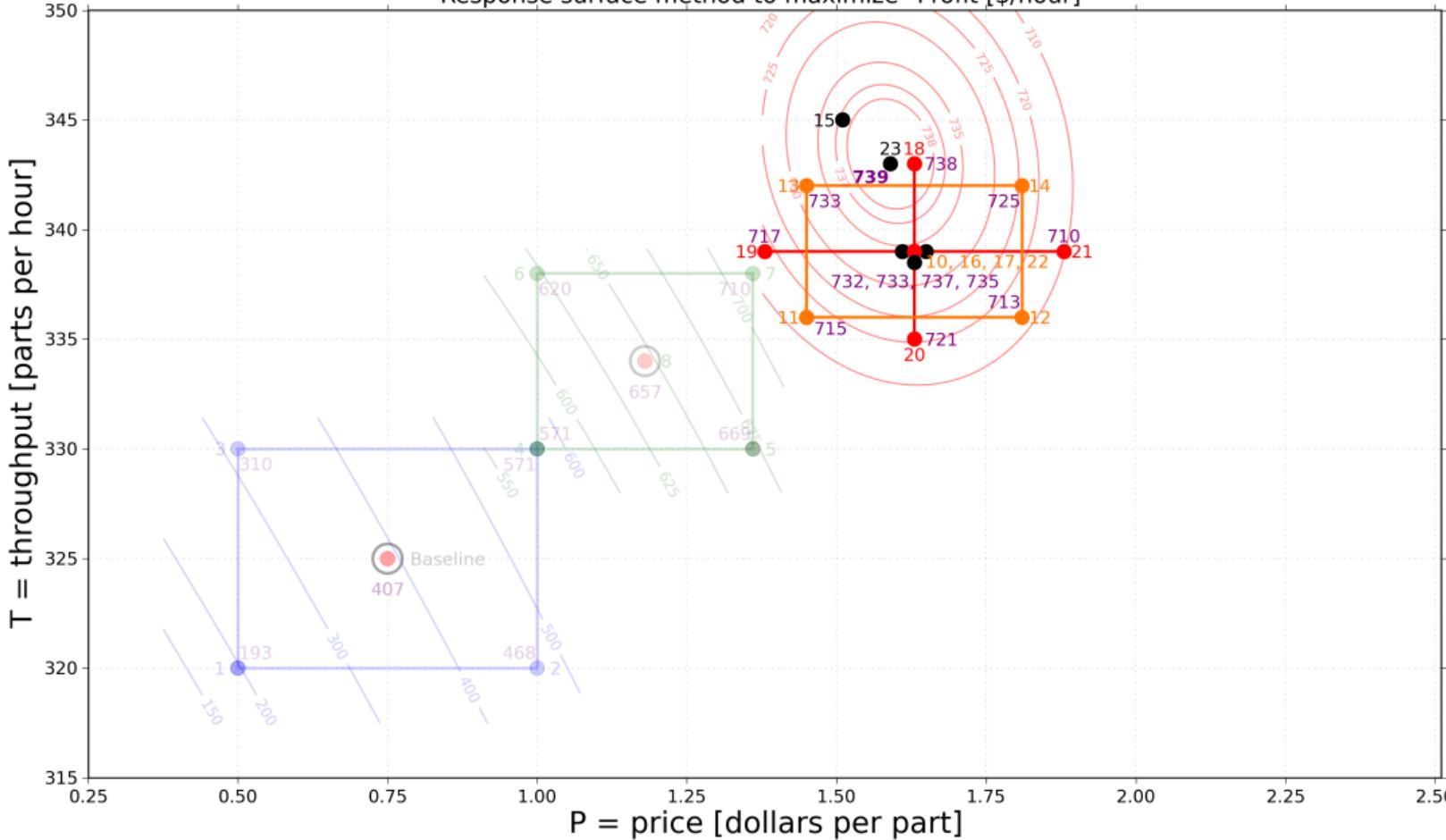
$$x_T^{(23)} = 1.46$$

$$T^{(23)} = 1.46 \cdot \frac{1}{2}(6) + 339 \approx 343 \text{ parts per hour}$$

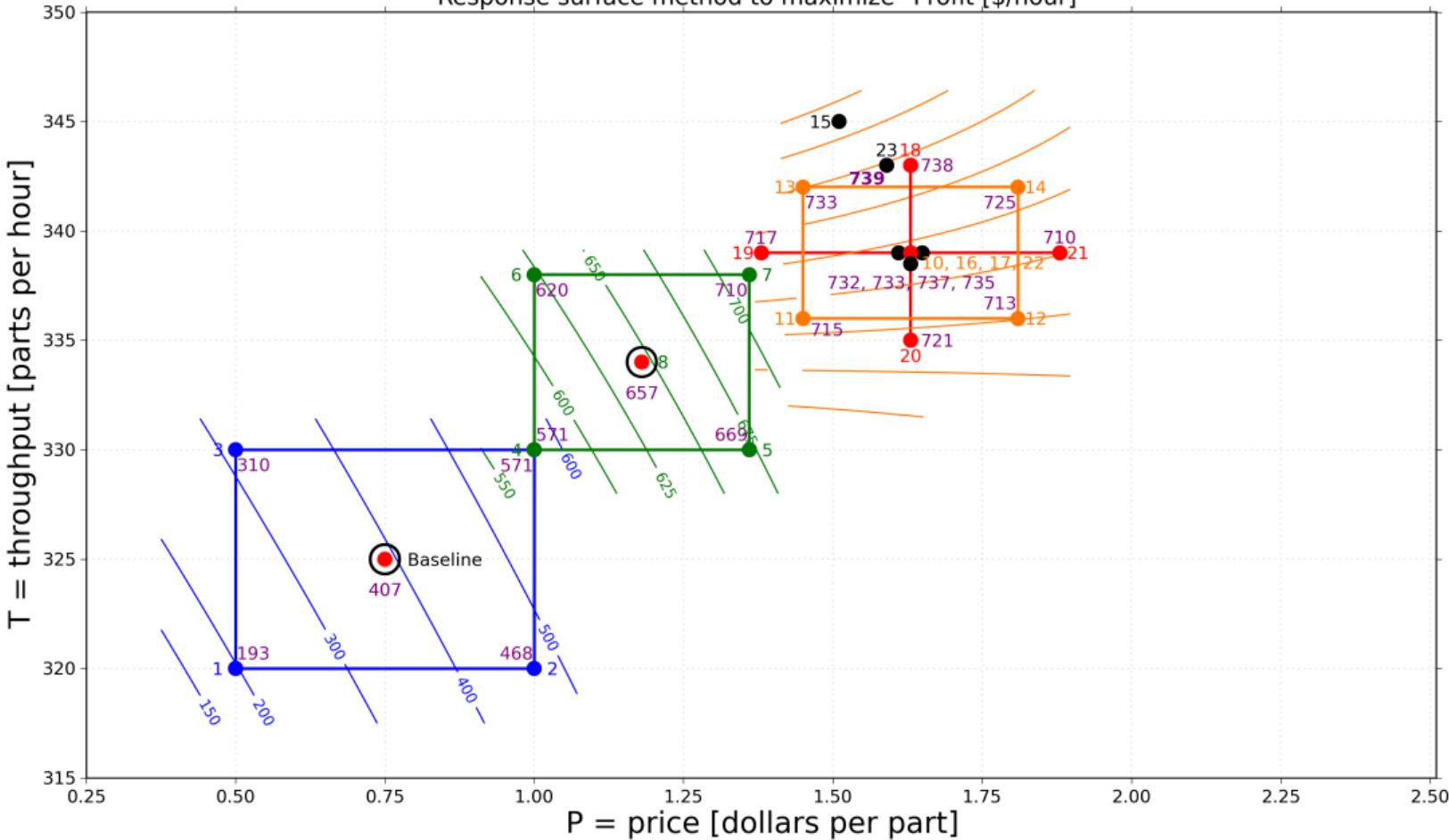
Response surface method to maximize "Profit [\$/hour]"



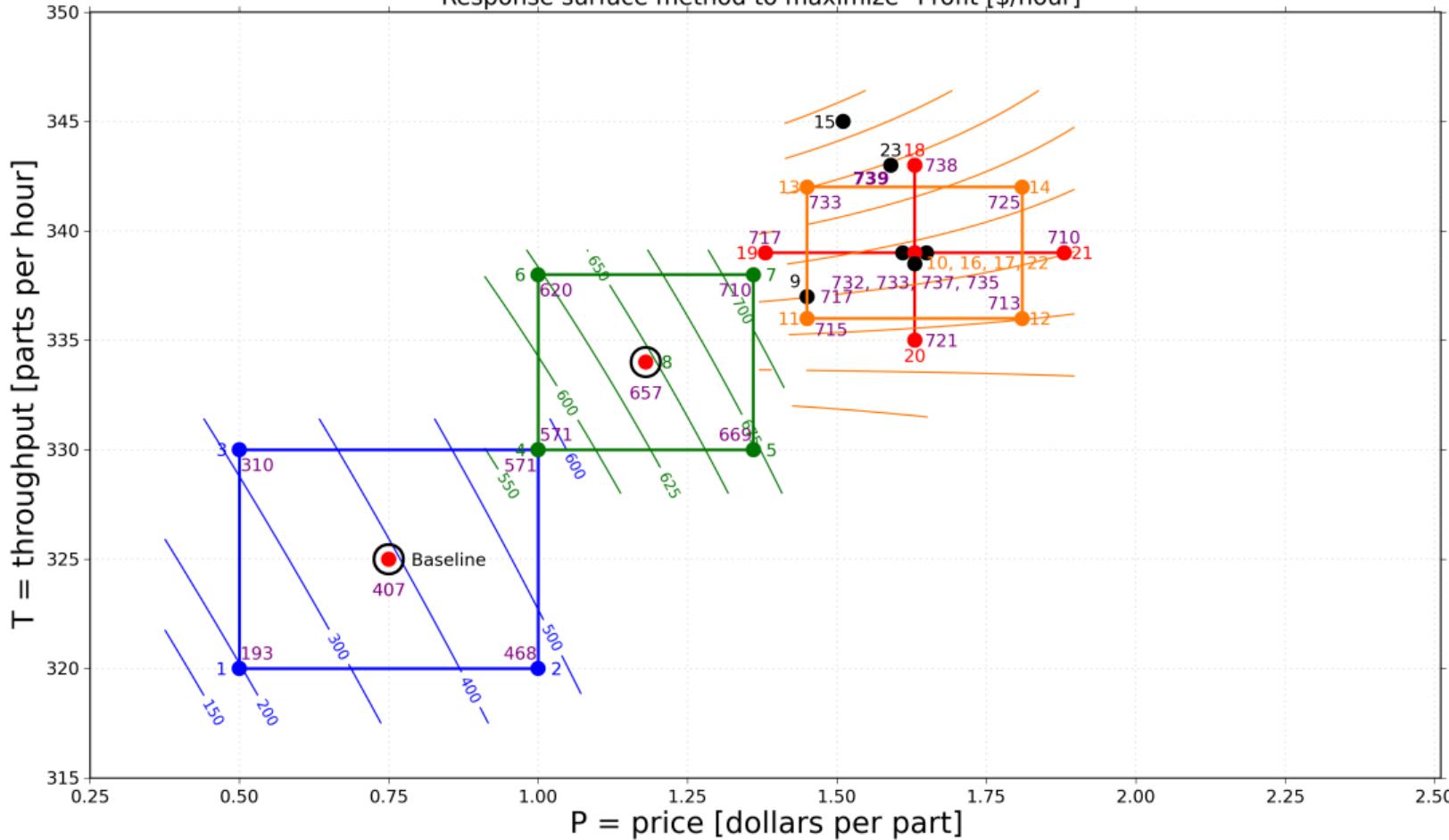
Response surface method to maximize "Profit [\$/hour]"



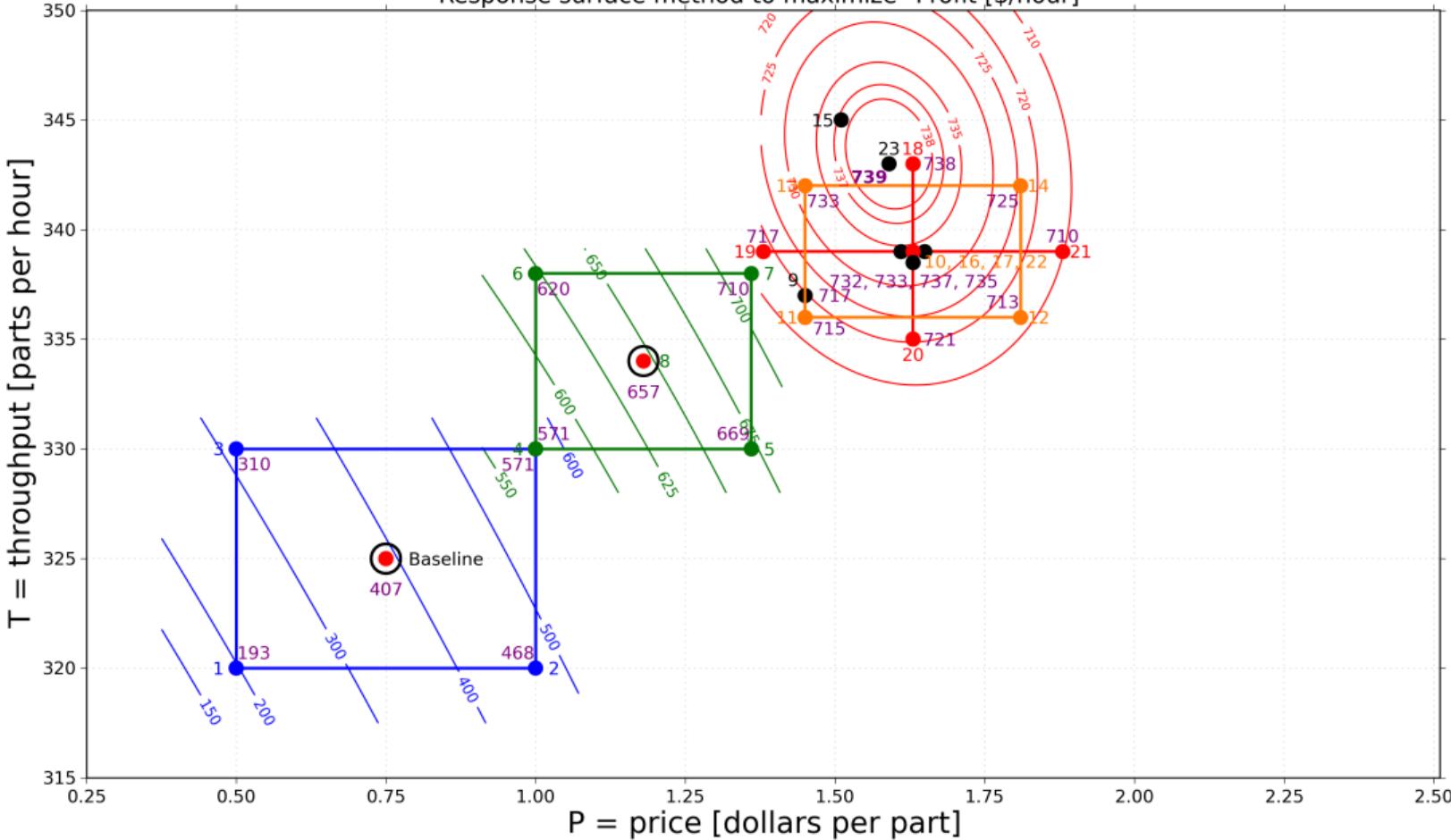
Response surface method to maximize "Profit [\$/hour]"



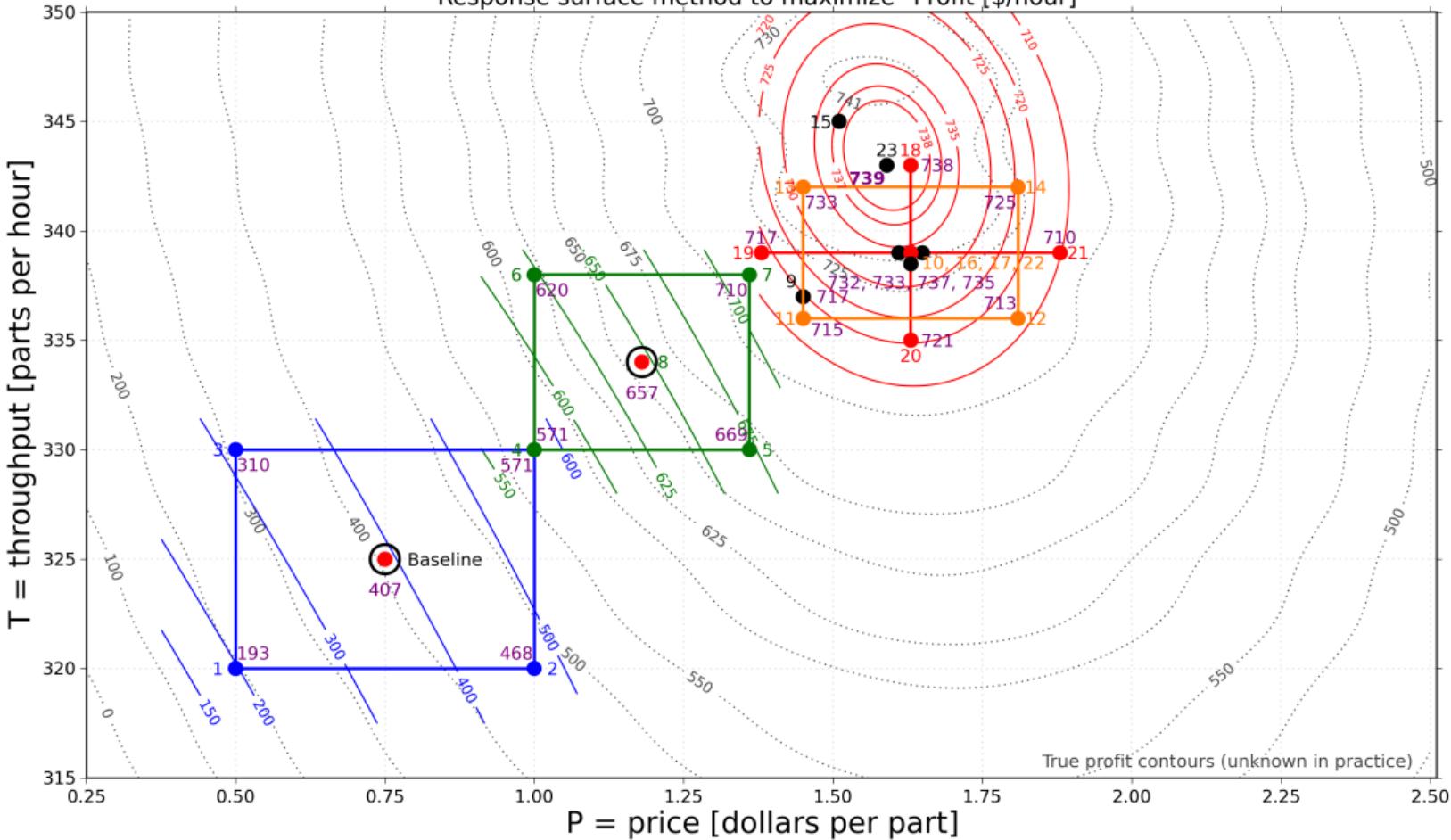
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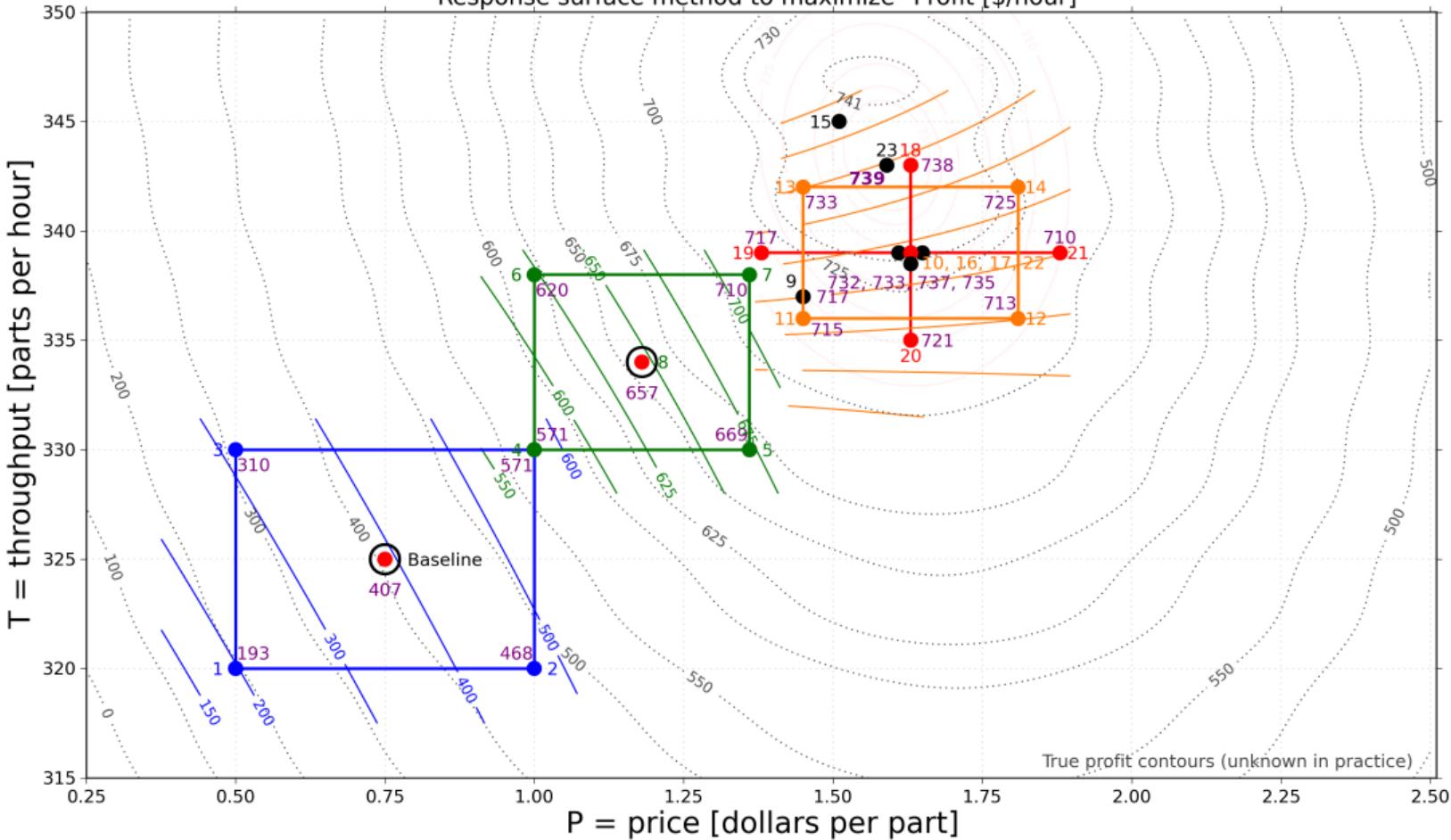
Response surface method to maximize "Profit [\$/hour]"



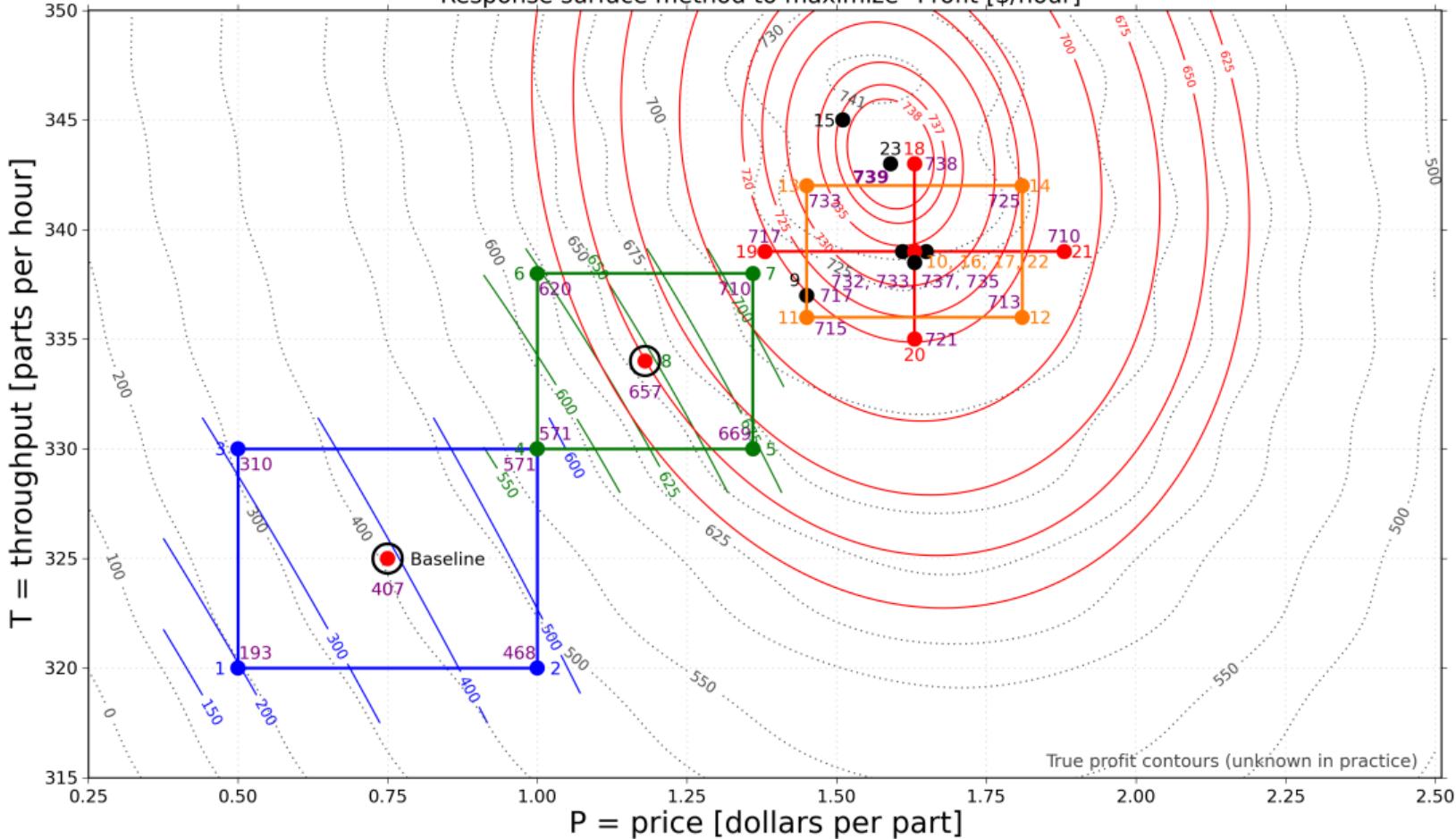
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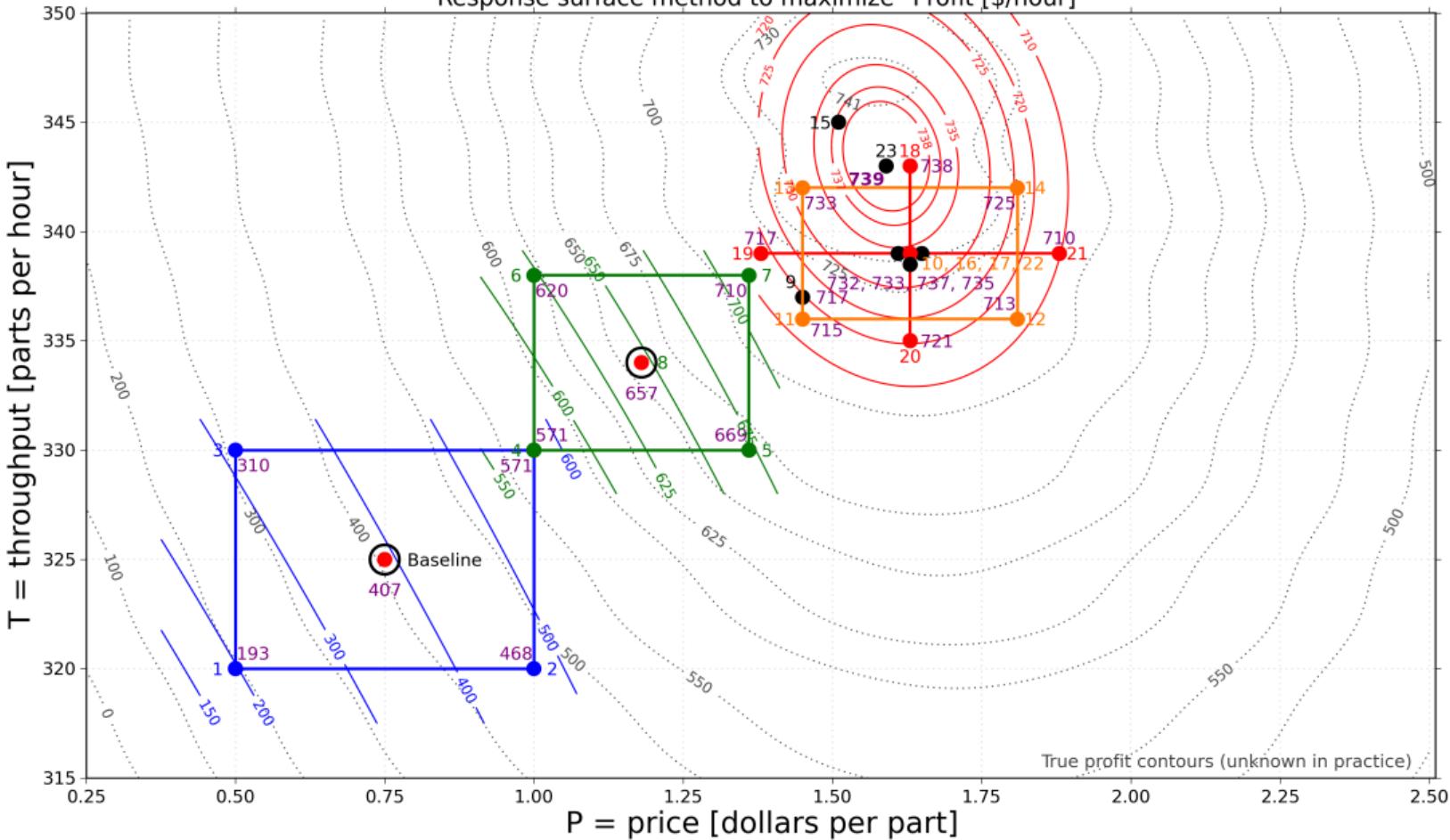
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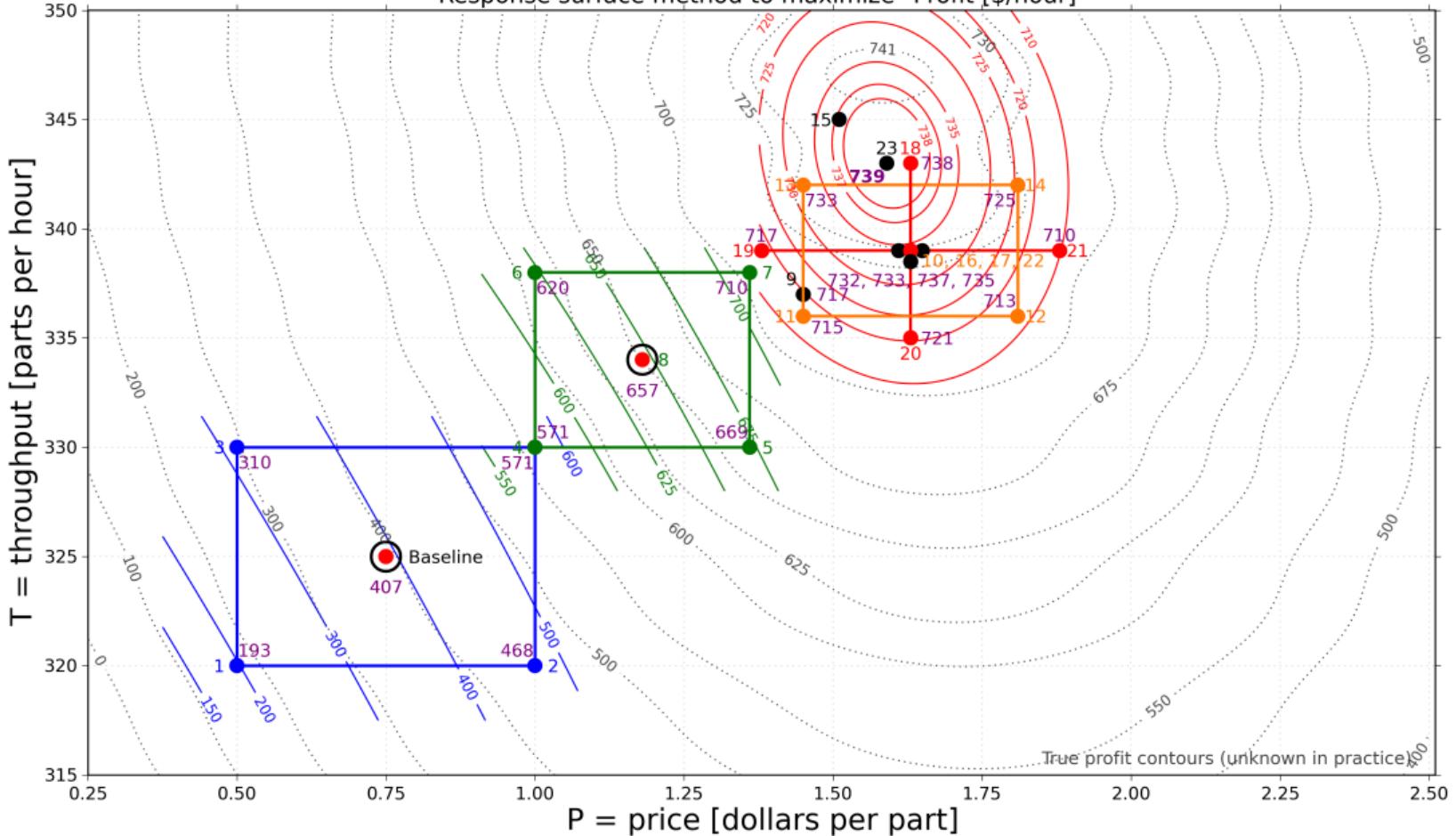
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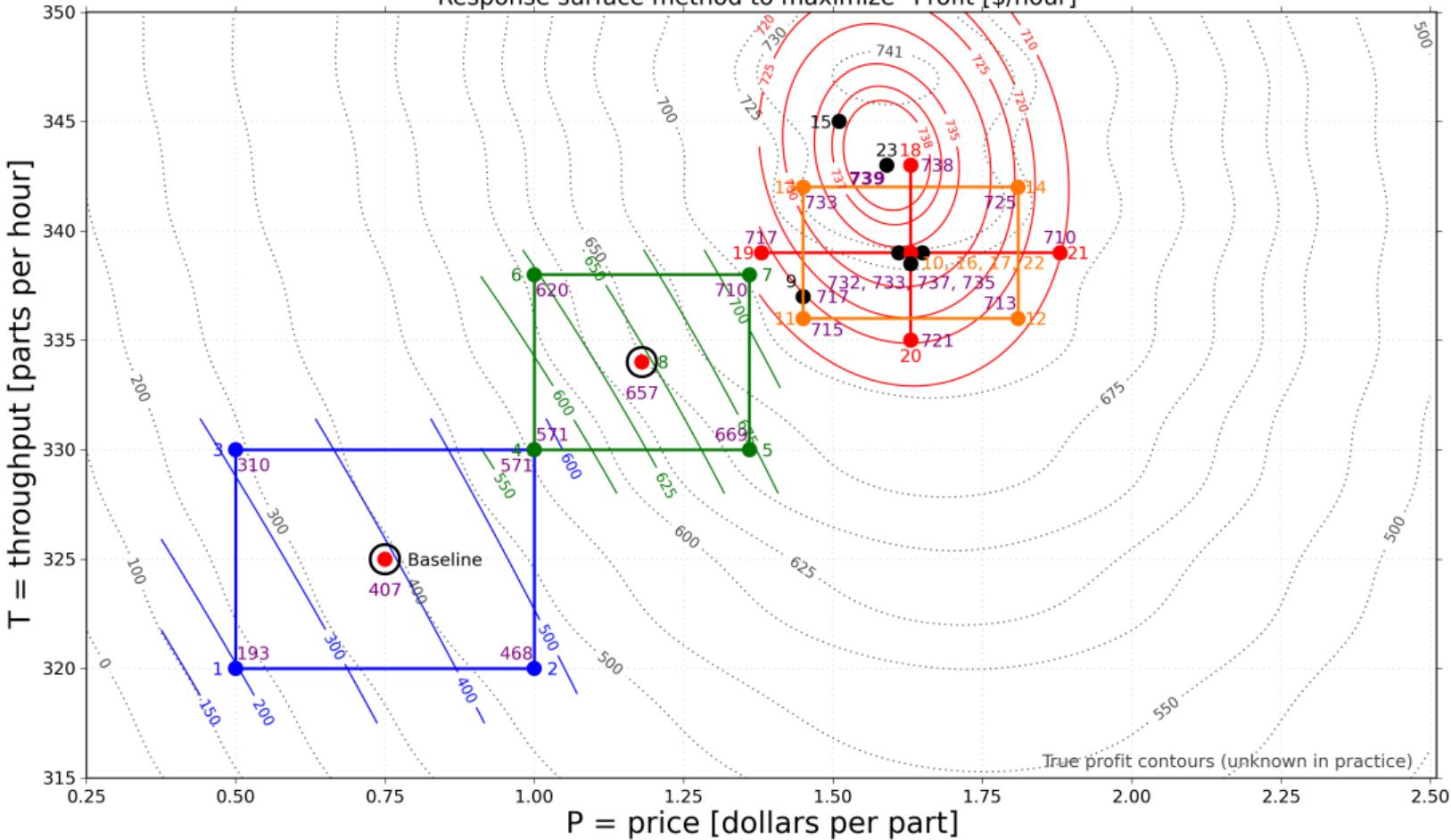
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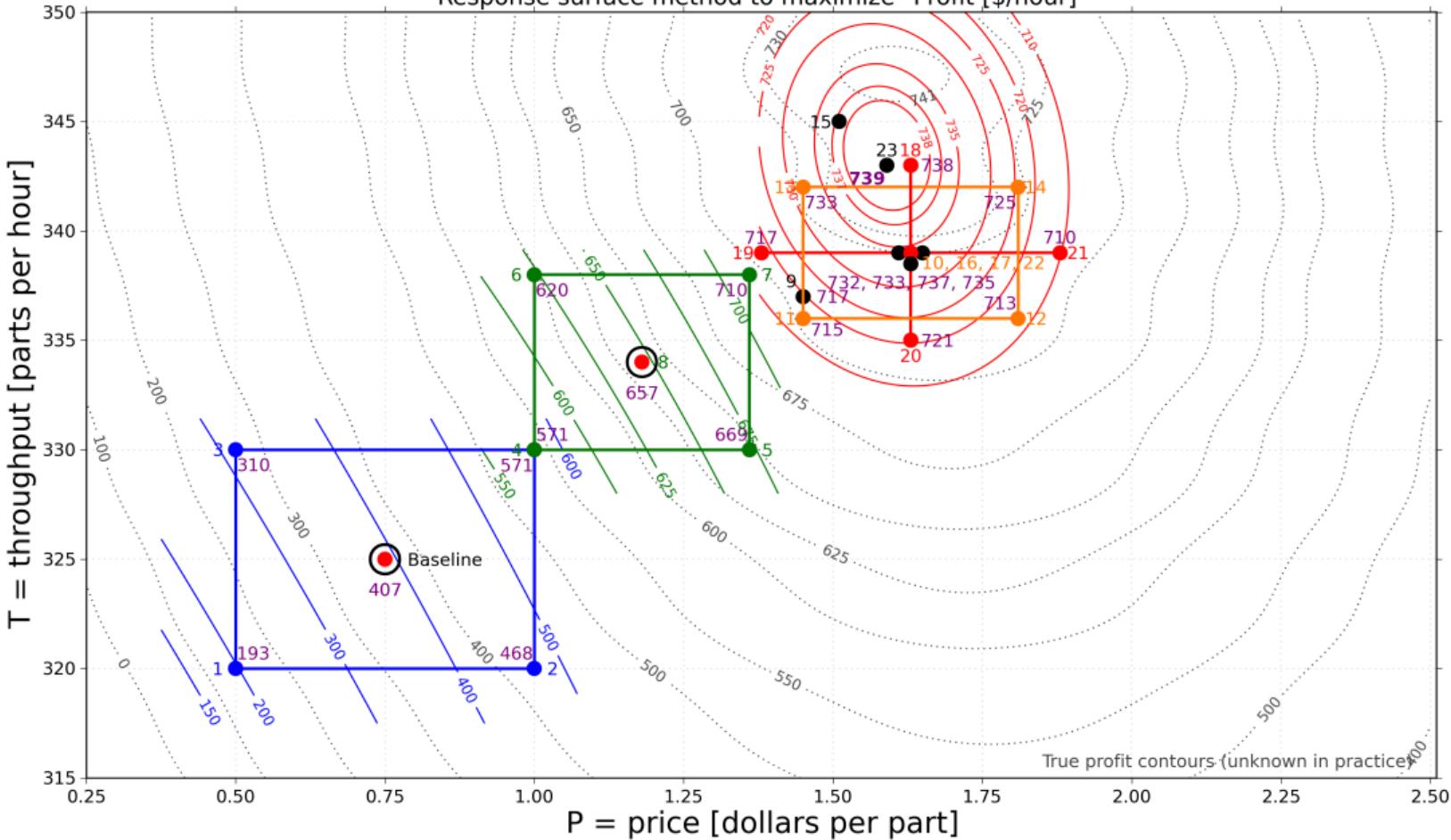
Response surface method to maximize "Profit [\$/hour]"



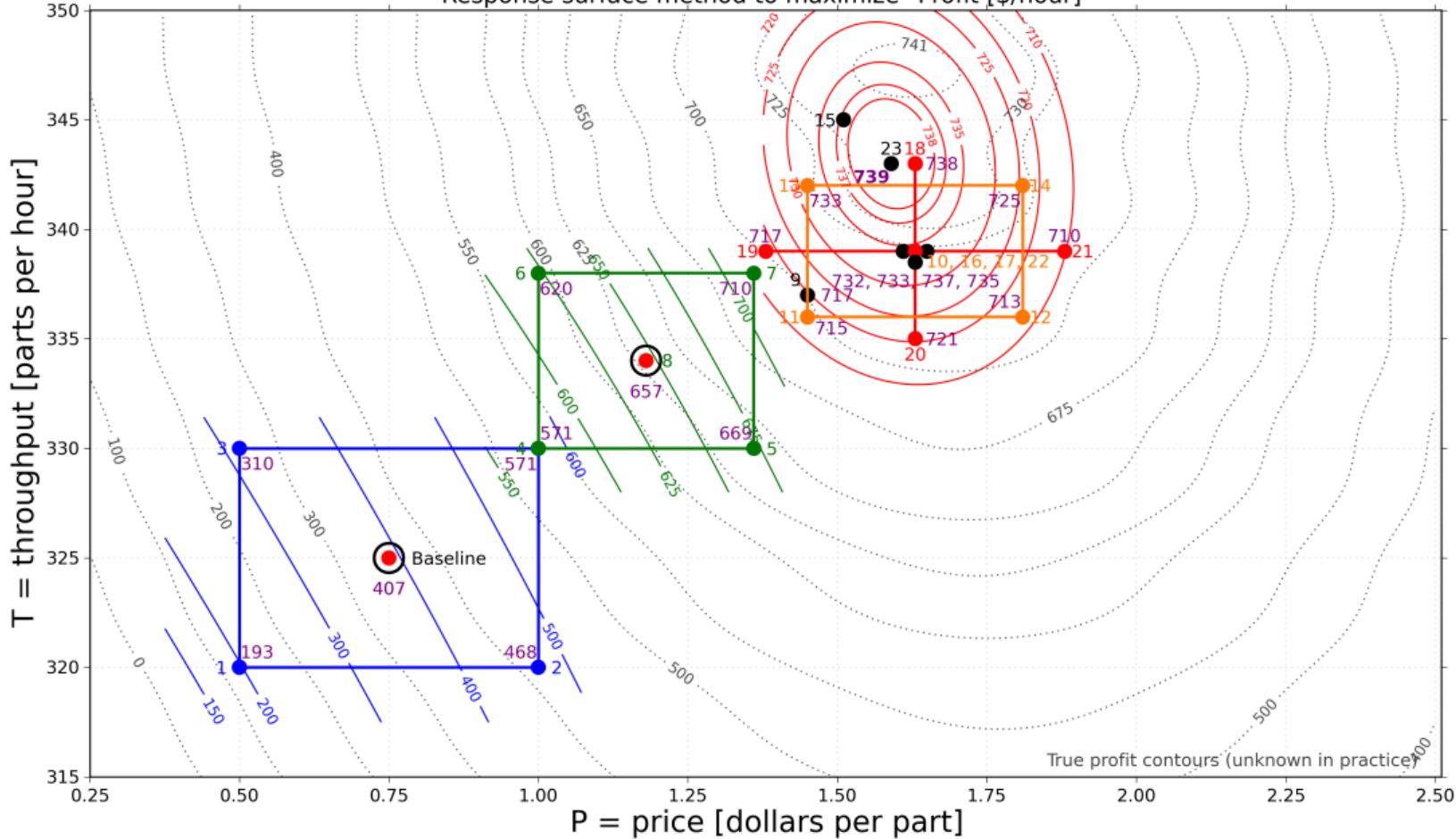
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