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*Escherichia coli* HGT – a novel  
high glucose throughput  
chassis especially designed for  
typical production conditions  
in large scale based on  
comprehensive systems  
biology studies

*Ralf Takors*

*July 20<sup>nd</sup>, 2017*

Systems &  
Synthetic Biology  
Meeting, Munich



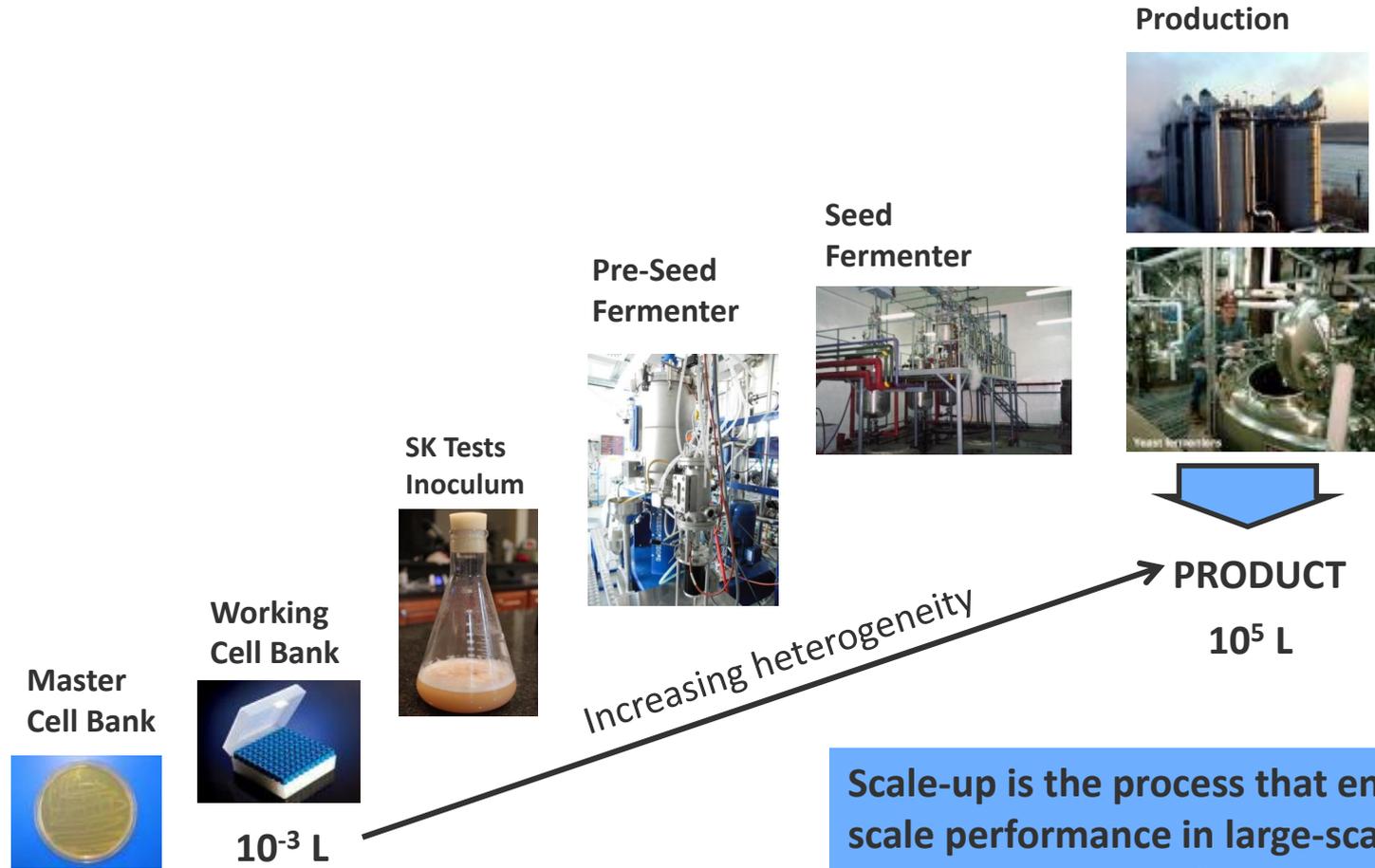
Scaling-up *E. coli*  
Modelling Strain Responses  
Conclusions for Strain Engineering  
Transferring Results

- Joana Simen
- Michael Löffler
- Alexander Niess

# Scaling Up

The way from the lab to the large-scale production

Takors, R (2015) *J. Biotechnol*



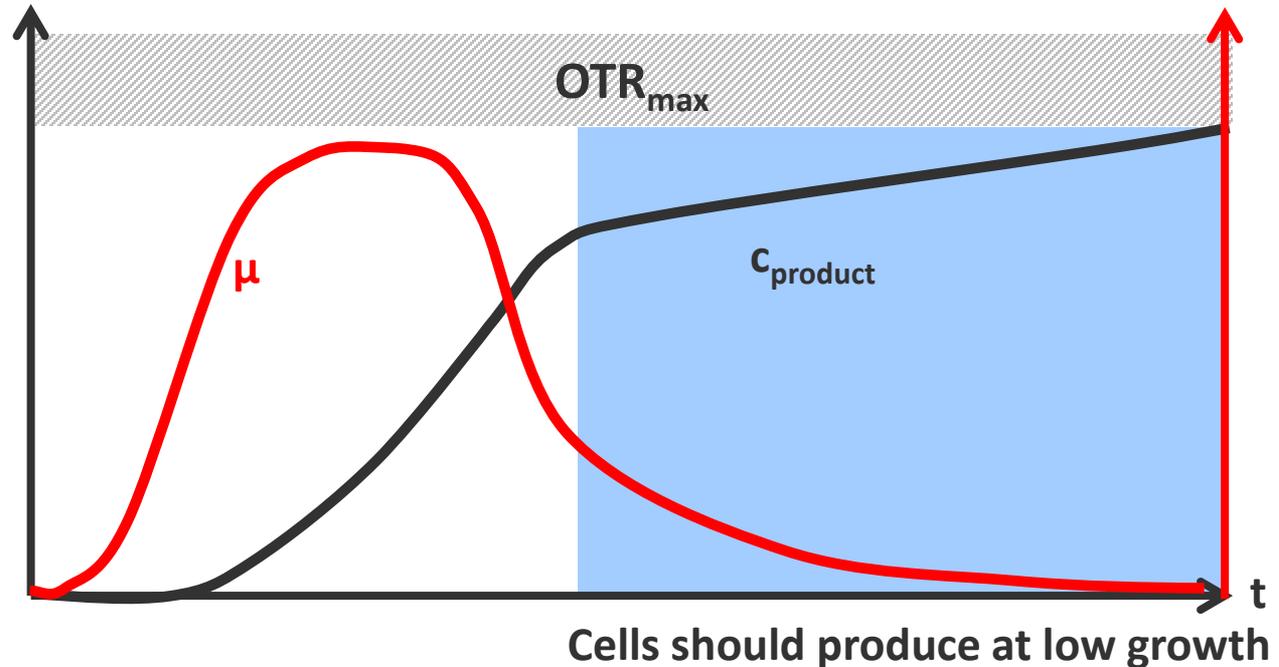
Scale-up is the process that enables lab-scale performance in large-scale, ensuring economic feasibility.

# Large Scale Constraints

Michalowski et al, 2017 *Metabolic Engineering*

- Oxygen transfer rate (**OTR**) is limited ( $\sim 150 - 180$  mmol/Lh)
- Cooling capacities are limited

But: productivities ( $\text{g/L}_{\text{reactor}}\text{h}$ ) should be maximized



# Ideal Strain for Large-Scale Application

The **ideal producer** should:

- enable high glucose uptake rates, even under resting condition
- be blind with respect to extracellular heterogeneities

**Goal:**

to create a novel *E. coli* chassis with fundamentally changed properties.

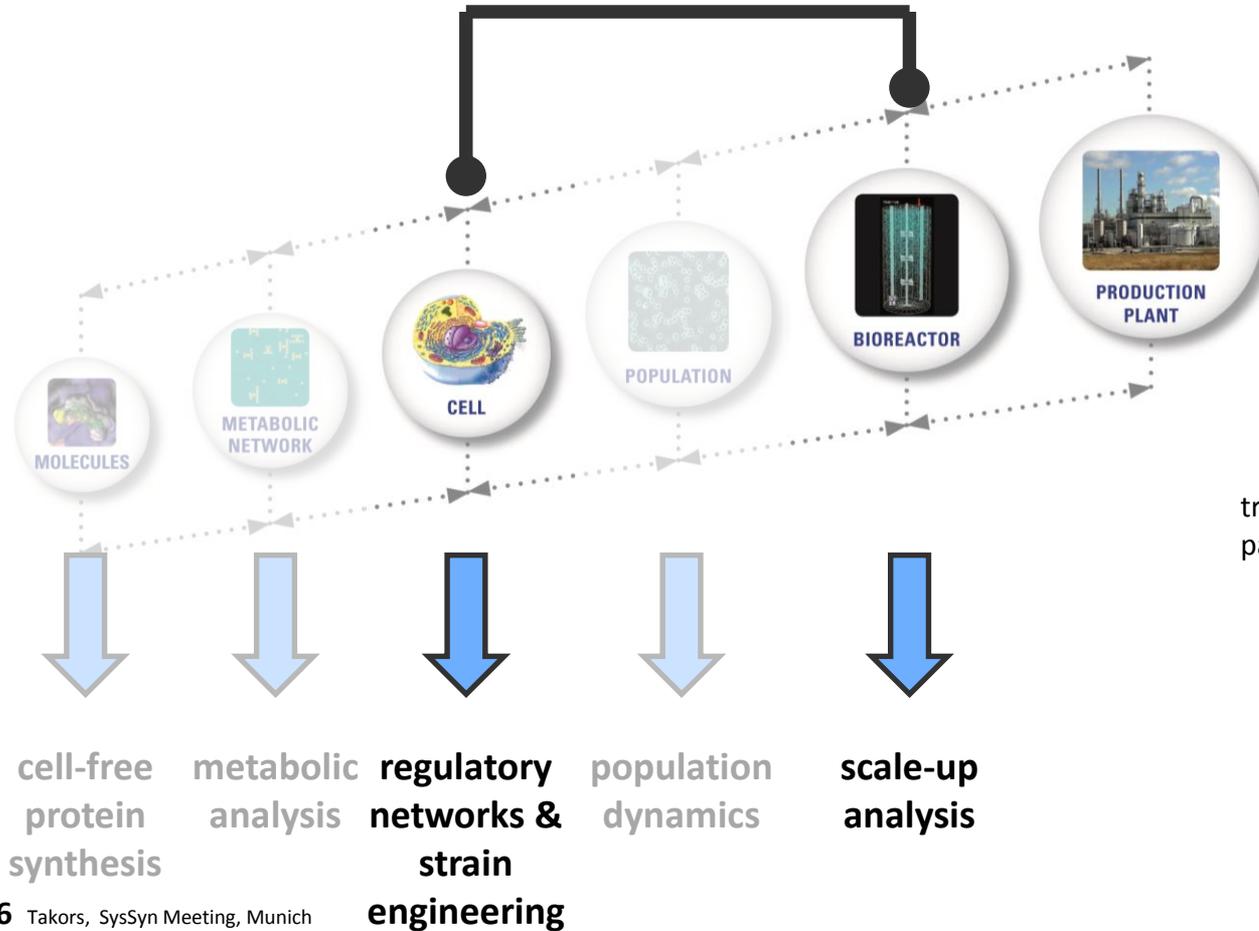
**Drawback:**

transcriptional responses under large-scale conditions not known

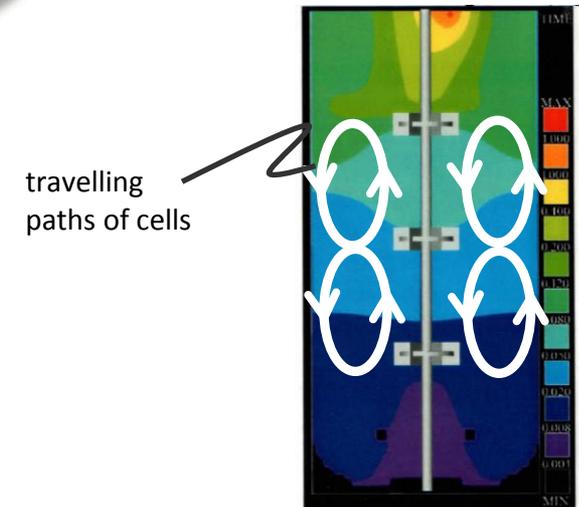
**Approach:**

To perform systems biology studies on large-scale performance for deriving guidelines for synthetic strain construction.

# Successful Bioprocess Development Needs to Pass Multiple Scales



What is the impact of repeated triggering on cellular performance?



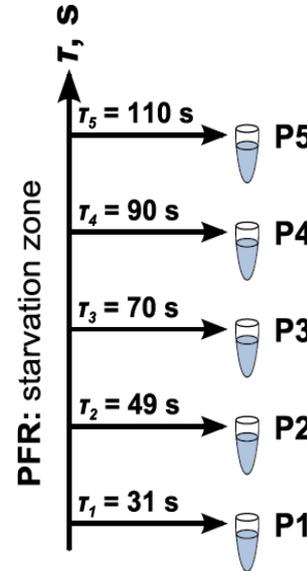
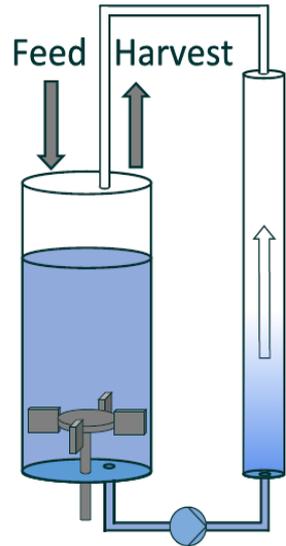
Simulated glucose distribution in 900 L stirred tank reactor  
Lapin et al., 2004

# Scaling-up *E. coli*

- Impact of Glucose Gradients on Cellular Performance -

- Development of a STR-PFR system to simulate oscillating gradients

STR  
(stirred tank reactor)



Short-term responses



Plug-flow like behavior  
( $\tau_{\text{PFR}} = 125 \text{ s}$ ,  $\text{Bo}=83$ )

- Volume PFR/ total volume: 25 %
- Online: temperature and oxygen
- thermally insulated

# STR-PFR Experiments With *E. coli*: Glucose Limitation

Simen, Löffler et al. 2016 *Metabolic Engineering*

## I Batch:

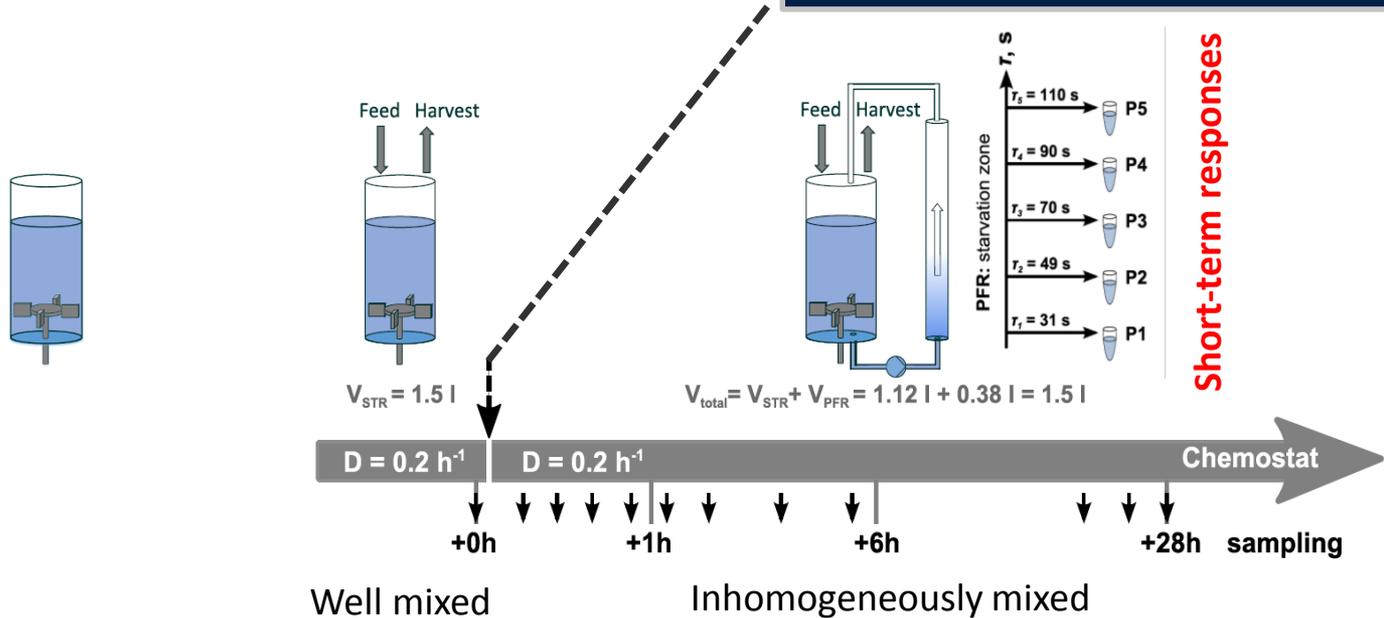
- $\mu = \mu_{max}$
- $V_{total} = V_{STR} = 1.5 \text{ l}$

## II Chemostat ( $\mu = 0.2 \text{ h}^{-1}$ )

- Steady-state (feed)
- $V_{total} = V_{STR} = 1.5 \text{ l}$

## III Chemostat ( $\mu = 0.2 \text{ h}^{-1}$ ) +PFR

- PFR: glucose starvation zone
- $V_{total} = V_{STR} + V_{PFR} = 1.12 \text{ l} + 0.38 \text{ l}$
- Residence time PFR 125 s



Long-term responses: 25 min 120 min

28 h

Glucose:

Short-Term Responses

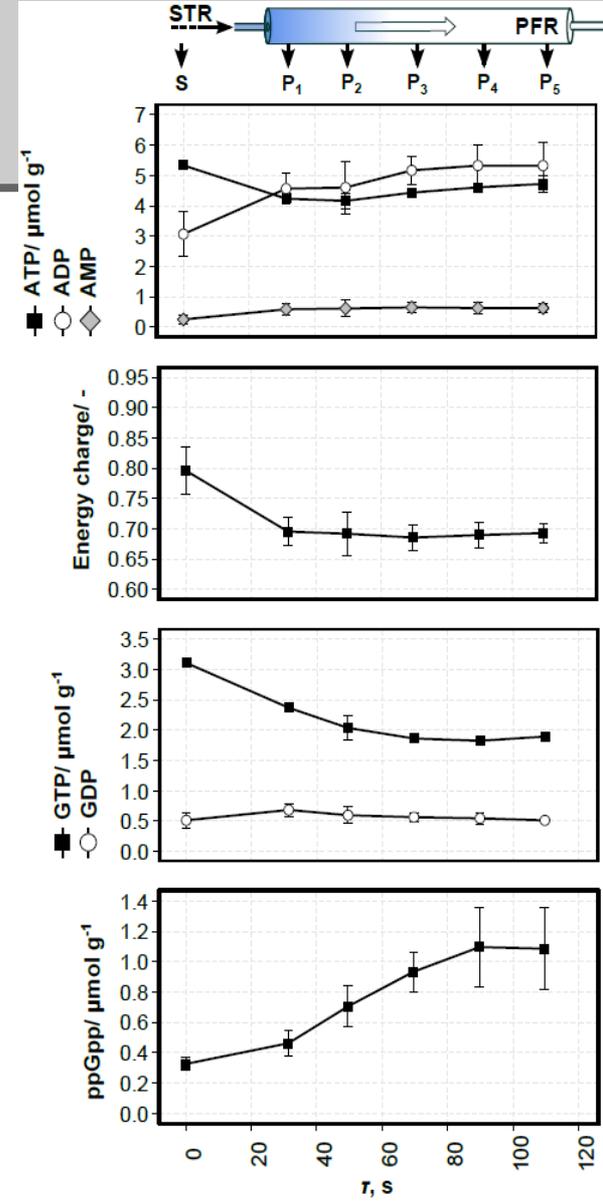
# Intracellular Nucleotides (Carbon Limitation-Starvation)

Simen, Löffler et al. 2016 *Metabolic Engineering*

- Decreasing intracellular ATP-Concentration
- Increasing ADP-Level
- Fast Energy charge reduction (30 sec)
- Decreasing GTP-Level
- Sigmoidal ppGpp accumulation

**Sequential response along the PFR**  
**< 30 sec: Reduced Energy charge**  
**< 70 sec: Decreasing GTP-Level**  
**30-90 sec: Increasing ppGpp-Level**

**Transcriptional Response**



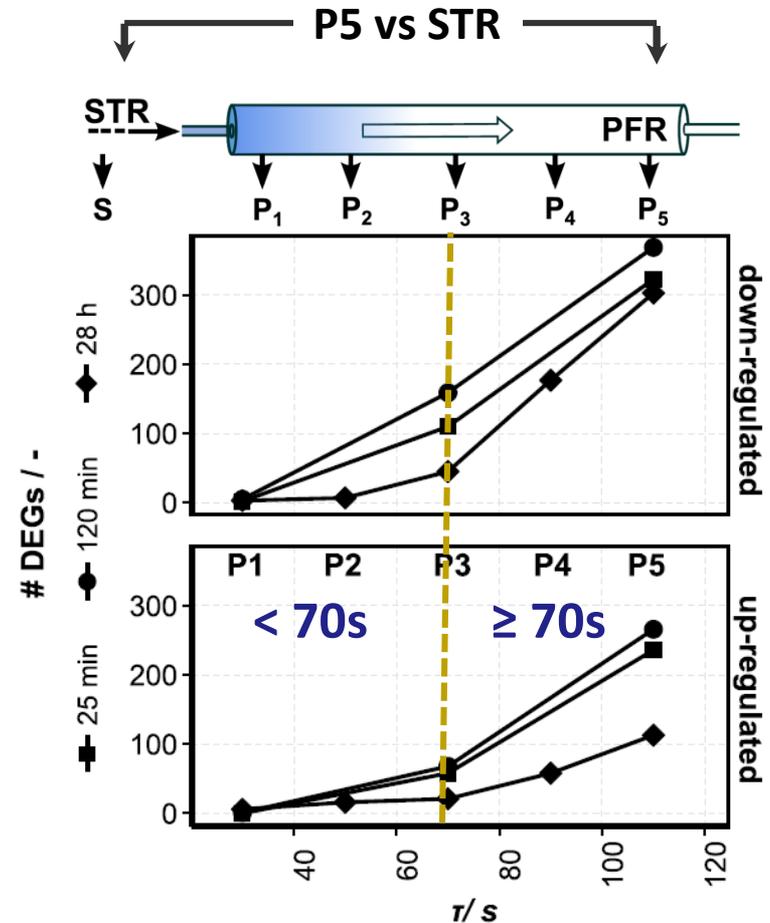
# Short-term Response on Glucose Limitation: Differentially Expressed (DE) Genes

Simen, Löffler et al. 2016 *Metabolic Engineering*

- Increasing limitation inside PFR
- Filter for DE genes
  - 1% false discovery rate
    - P5 down: 836
    - P5 up: 955
  - Fold change >1.5 fold
    - P5 down: 369
    - P5 up 266

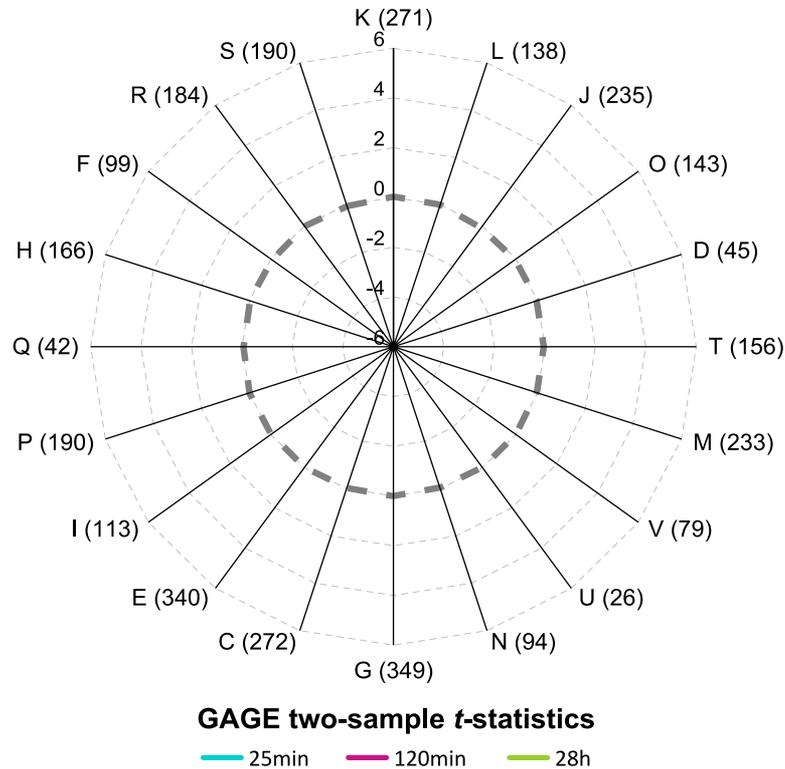
→ Immediate DE response after entering PFR

- ,slow' dynamics < 70 s
- Transcriptional boost > 70 s



# Differentially Expressed Genes (PFR outlet vs STR)

Simen, Löffler et al. 2016 *Metabolic Engineering*



## Information storage and processing

- K Transcription
- L Replication, recombination and repair
- J Translation, ribosomal structure and biogenesis

## Cellular processes and signaling

- O Posttranslational modification, protein turnover and chaperones
- D Cell cycle control, cell division and chromosome partitioning
- T Signal transduction mechanisms
- M Cell wall, membrane, envelope biogenesis
- V Defense mechanisms
- U Intracellular trafficking, secretion, vesicular transport
- N Cell motility

## Metabolism

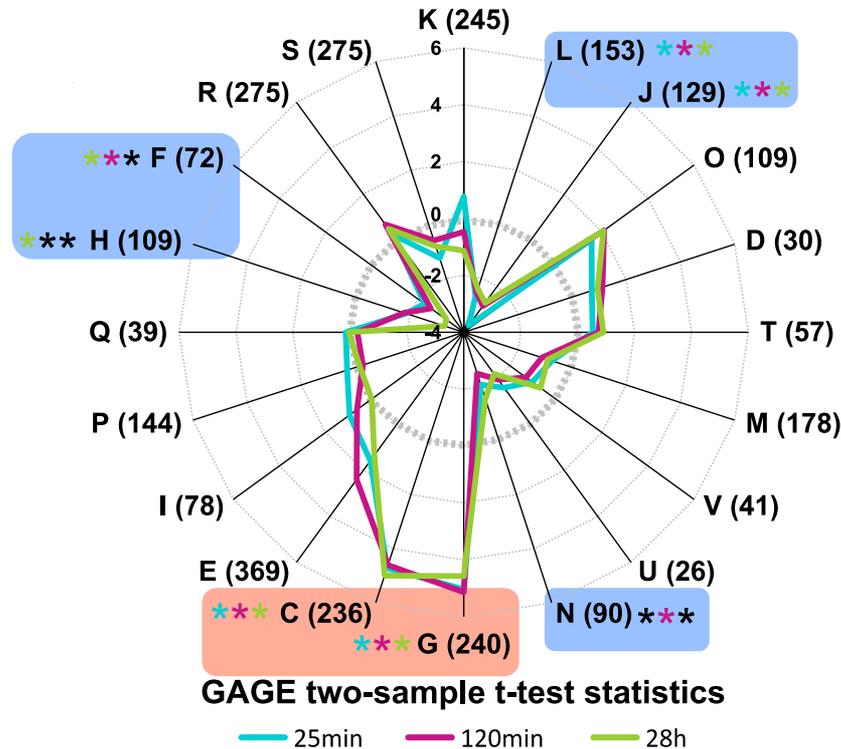
- G Carbohydrate transport and metabolism
- C Energy production and conversion
- E Amino acid transport and metabolism
- I Lipids transport and metabolism
- P Inorganic ion transport and metabolism
- Q Secondary metabolites biosynthesis, transport and metabolism
- F Nucleotide transport and metabolism
- H Coenzyme transport and metabolism

## Poorly characterized

- R General function prediction only
- S Function unknown

# Differentially Expressed Genes (PFR outlet vs STR): 25, 120 min, 28h

Simen, Löffler et al. 2016 *Metabolic Engineering*



## INFORMATION STORAGE AND PROCESSING

[K] Transcription

[L] Replication/recombination/repair

[J] Translation/ribosomal structure/biogenesis

## CELLULAR PROCESSES AND SIGNALING

[O] Posttranslational modification/protein turnover/chaperones

[D] Cell cycle control/cell division/chromosome partitioning

[T] Signal transduction mechanisms

[M] Cell wall/membrane/envelope biogenesis

[V] Defense mechanisms

[U] Intracellular trafficking/secretion/vesicular transport

[N] Cell motility

## METABOLISM

[G] Carbohydrate transport and metabolism

[C] Energy production and conversion

[E] Amino acid transport and metabolism

[I] Lipid transport and metabolism

[P] Inorganic ion transport and metabolism

[Q] Secondary metabolites biosynthesis/transport/catabolism

[F] Nucleotide transport and metabolism

[H] Coenzyme transport and metabolism

## POORLY CHARACTERIZED

[R] General function prediction only

[S] Function unknown

## General finding:

→ induction of carbon import, metabolism and energy generation

→ repression of energy intensive processes

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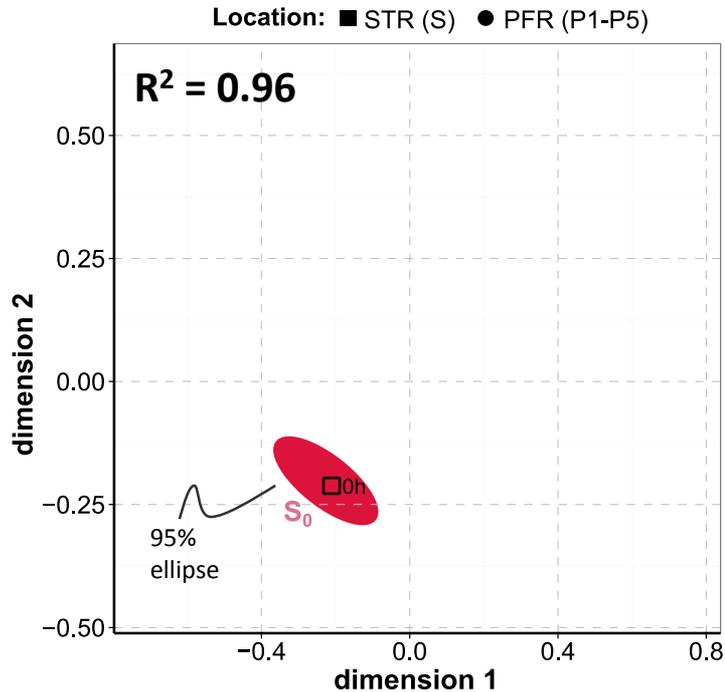
Glucose:

Long-Term Responses

# Long-Term Response on Glucose Gradients (triplicate results):

Reference – before connection with PFR

Simen, Löffler et al. 2016 *Metabolic Engineering*

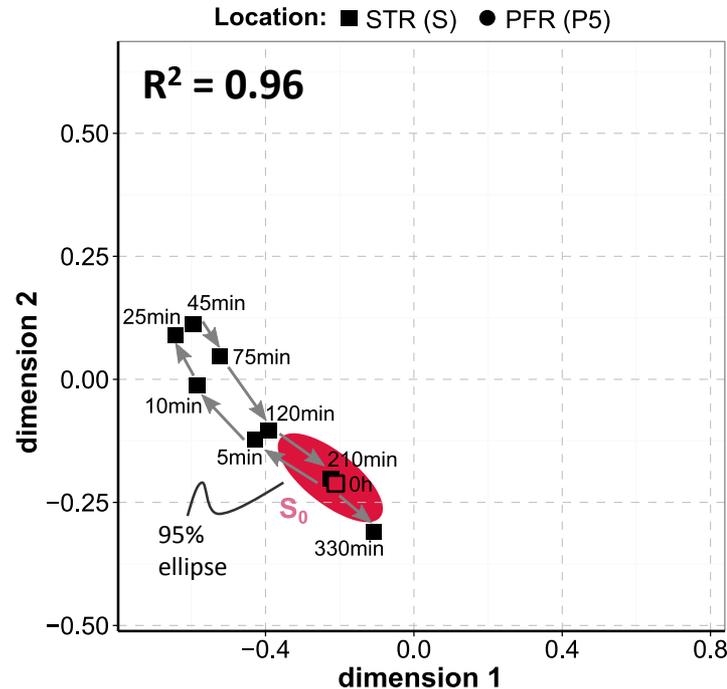


- distinct initial state  $S_0$  in STR

# Long-Term Response on Glucose Gradients (triplicate results):

Phase I after connection with PFR

Simen, Löffler et al. 2016 *Metabolic Engineering*

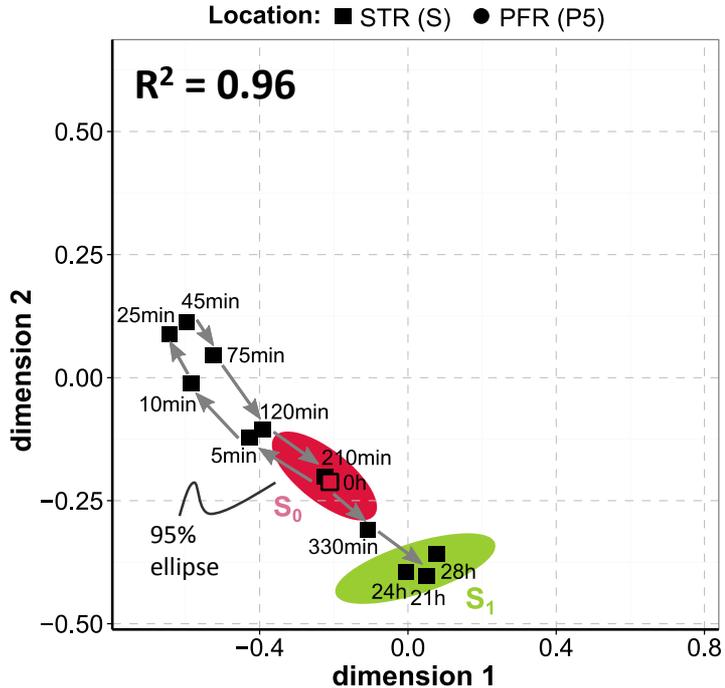


- distinct initial state  $S_0$  in STR
- strong transcriptional changes after PFR connection

# Long-Term Response on Glucose Gradients (triplicate results):

Phase II after connection with PFR

Simen, Löffler et al. 2016 *Metabolic Engineering*

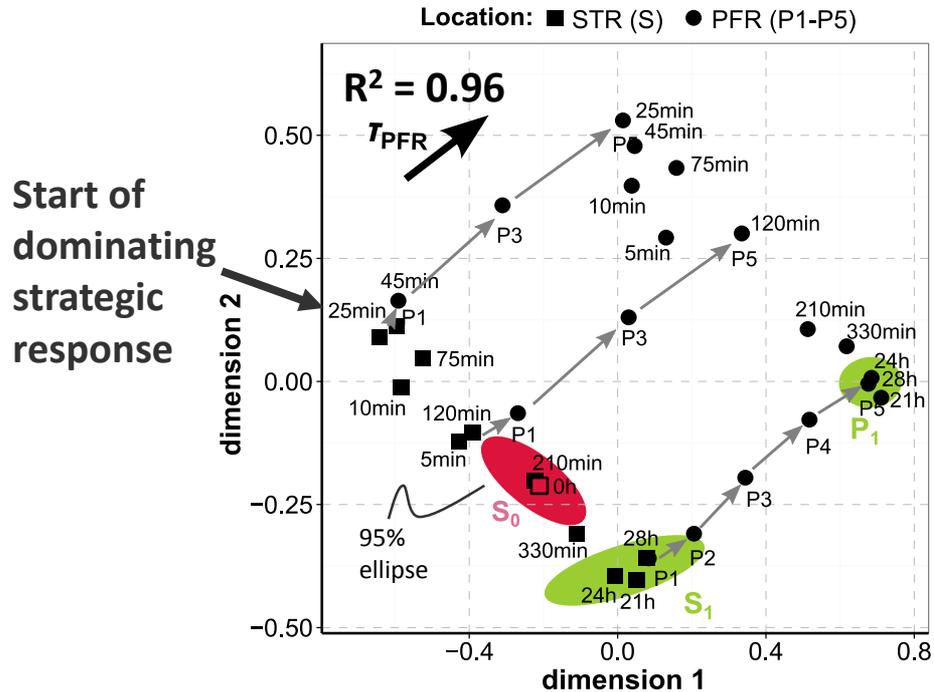


- distinct initial state  $S_0$  in STR
- strong transcriptional changes after PFR connection
- transcriptional changes converge to a new steady-state

# Long-Term Response on Glucose Gradients (triplicate results):

Repeated Transcriptional Shifts from STR to PFR

Simen, Löffler et al. 2016 *Metabolic Engineering*



- distinct initial state  $S_0$  in STR
- strong transcriptional changes after PFR connection
- transcriptional changes converge to a new steady-state
- gradients in PFR cause trackable transcriptional changes leading to a stable distribution of transcriptional patterns

Gradients cause massive, periodic on-/off-switching of genes finally leading to stable transcriptional patterns coexisting next to each other

# What can we learn from modelling?

What can we learn from modelling?

Predicting the Transcriptional Dynamics

## Agent (single cell)

- polymerase movement: constant elongation rate
  - constraint: minimum distance between ribosomes
- attenuation modelling neglected for simplification
  - Simplification: start only valid under nitrogen limitation
  - Transcription and translation are closely coupled
- Number of ribosomes per gene is variable and specific for the gene
- mRNA degradation considered with constant degradation elongation rate, initiated at start codon of transcription
- No protein degradation, only dilution by growth

## Population (STR-PFR operating in continuous mode)

- STR = ideally mixed; PFR = plugflow reactor
- Population balances:
  - (1) PFR entering
  - (2) drained off by efflux
  - (3) cell division, no initiation of transcription
- Fate of 10.000 cells was tracked

Number of likely events per time:

$$\alpha_1 = N_{STR} \frac{\dot{V}_{PFR}}{V_{STR}}$$
$$\alpha_2 = N_{STR} \frac{\dot{V}_{Feed}}{V_{STR}}$$
$$\alpha_3 = N_{STR}^0 D$$

Gillespie algorithm:

$$\tau = \frac{1}{\sum \alpha_i} \ln \left( \frac{1}{r_1} \right)$$
$$\sum_{j=1}^{i-1} \alpha_j \leq r_2 \leq \sum_{j=1}^i \alpha_j$$

# Simulation Parameters – No Regression

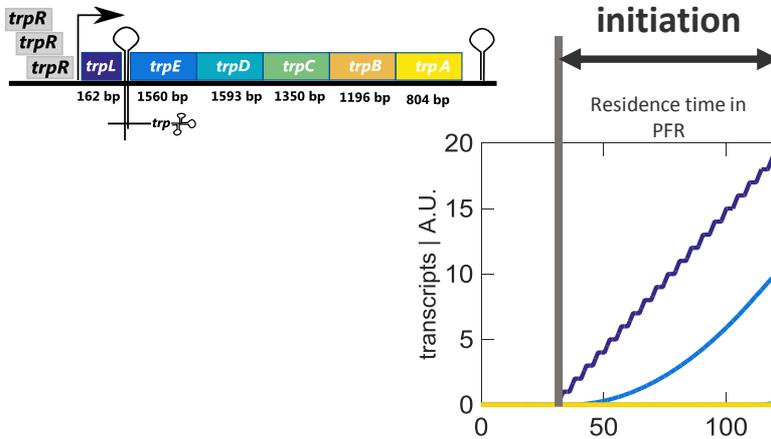
Niess et al. .2017. *Frontiers in Microbiology*

Parameter	Value	Unit	
$v_{elo}^{RNAP}$	21	Nucleotides per second	Elongation rate
$v_{elo}^{Ribosome}$	21	Nucleotides per second	Ribosome movement on mRNA
$v_{elo}^{RNase}$	21	Nucleotides per second	RNase degradation rate
$\Delta x$	100	Nucleotides	Minimum distance between two RNAPs
$\Delta y$	100	Nucleotides	Minimum distance between ribosomes
$\Delta z$	100	Nucleotides	Closest distance of RNase to ribosome
$t_{ind}$	[30 125]	Seconds	Induction period
$\dot{V}_{PFR}$	180	$\text{mL min}^{-1}$	Flow through PFR
$\dot{V}_{Feed}$	5	$\text{mL min}^{-1}$	Feed
$V_{STR}$	1,120	mL	STR volume
$D$	0.2	$\text{h}^{-1}$	Dilution rate of the system
$N_{STR}^0$	10,000	cells	Total number of tracked cells

# Once Initiated, Transcriptional (TC) Stimulus Propagates From PFR into STR Followed by Translation (TL): Example TRP Operon

Induction of *trp* operon during N-limitation

Niess et al. .2017. *Frontiers in Microbiology*



## Key findings:

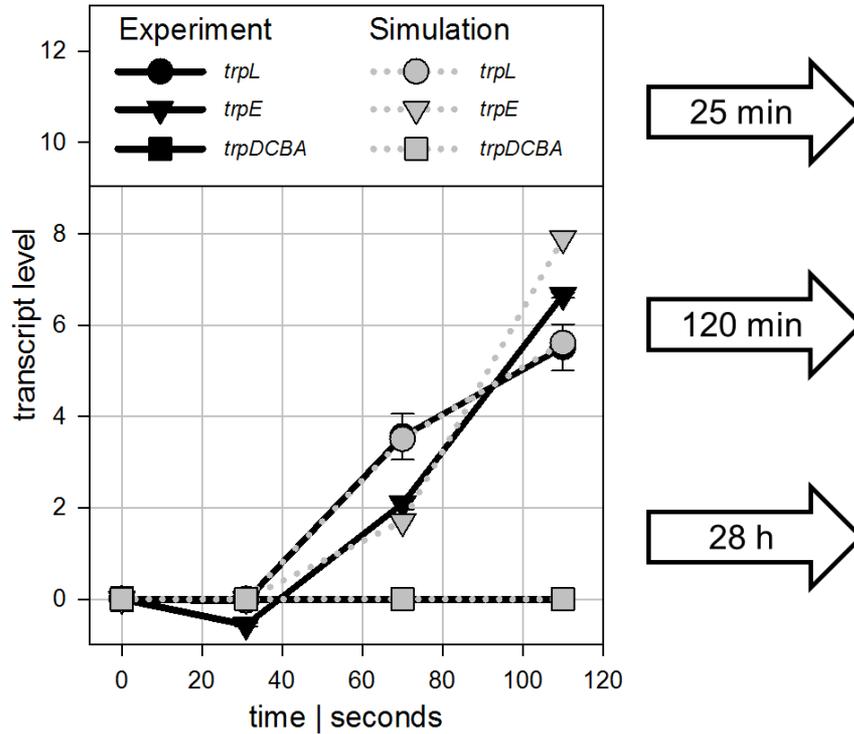
- Once initiated in PFR, transcription and translation continues in STR
- Mayor burden is located in STR
- Cells with different transcriptional patterns co-exist next to each other: population heterogeneity

# Prediction of population transcript levels in STR

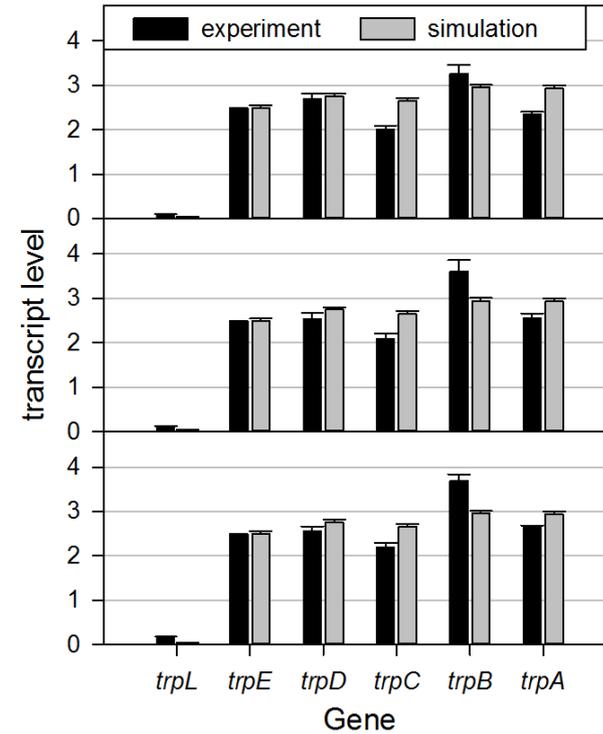
Agent based modeling tracking the fate of 10.000 cells

Niess et al. .2017. *Frontiers in Microbiology*

### Dynamic along PFR



### Distribution in STR



What can we learn from modelling?

Deriving Constraints for Creating Robust Strains  
For Large-Scale Application

# Modeling Assumptions for Estimating Cellular Efforts Periodically Switching Genes ON/OFF

Simen, Löffler et al. 2016 *Metabolic Engineering*

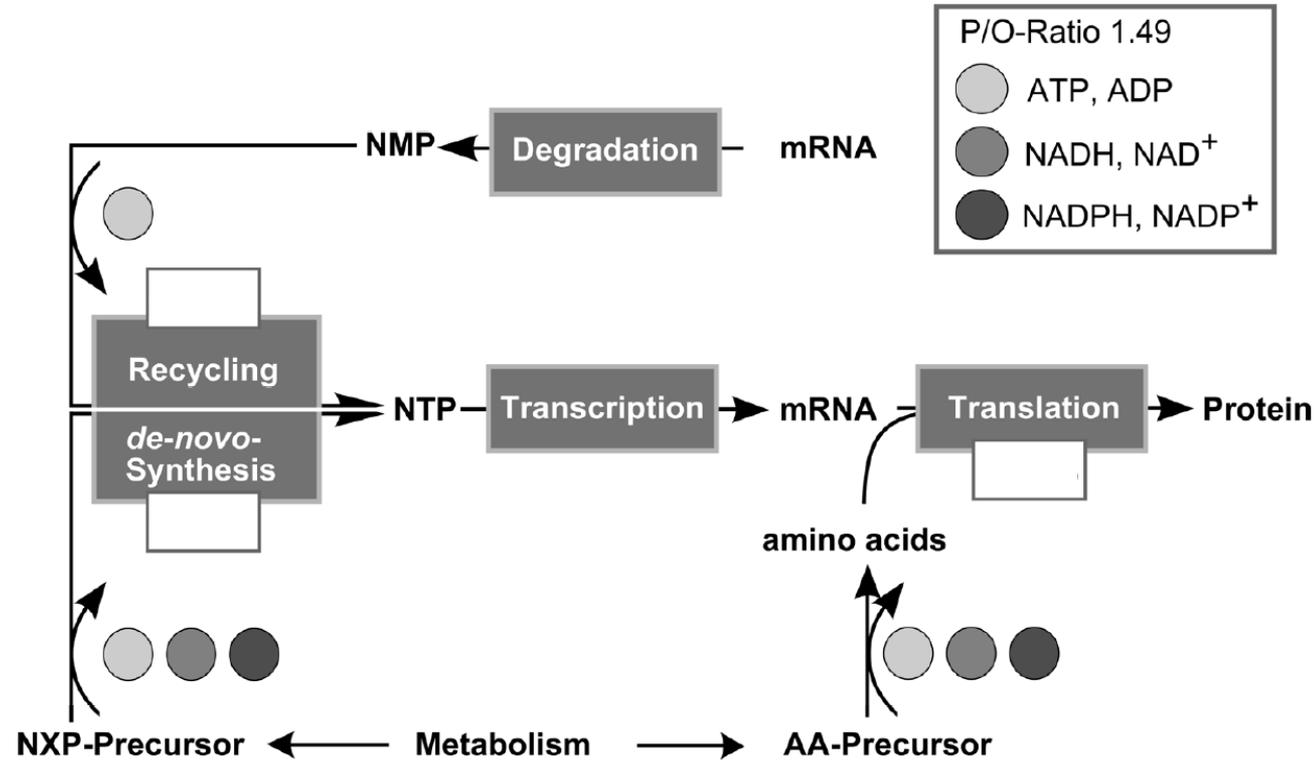
- Select transcripts with **FDR < 1%**
- Group in **up-** and **downregulated** genes
- *De novo* precursor synthesis:
  - calculate individual ATP needs for G, A, T, C formation from metabolic precursors
  - calculate ATP needs for amino acid production assuming average protein composition
- **Transcription:** For each mRNA with individual G, A, T, C content: 2 ATP/nucleotide
- **Translation:** 4 ATP/amino acid
- Considering mRNA dynamics and PFR residence time: **11 ribosomes per mRNA**
- **Completing translation** after recycling in STR

# Modeling Additional ATP Costs for Transcription and Translation

Individual ATP balances for each gene, reference: native maintenance

Simen, Löffler et al. 2016 *Metabolic Engineering*

ATP cost reference: *E. coli* maintenance (Taymaz-Nikerel et al. 2010)



**Maintenance demands are increased by 40 – 50 % in large-scale!  
Represents missing energy for hyperproducers.**

# Exploiting the Results: Identifiers for Smart Genome Reduction

## Top 20 Gene Targets for Deletion/Modulation Saving ATP

Simen, Löffler et al. 2016 *Metabolic Engineering*

Gene <sup>†</sup>	Percentage increasing the growth-independent maintenance, %			COG	Function
	De novo mRNA synthesis	Translation	$\Sigma$		
<i>fliC</i>	2.70	0.40	3.10	N	flagellar biosynthesis; flagellin, filament structural protein
<i>aroF</i>	0.67	0.10	0.77	E	2-dehydro-3-deoxyphosphoheptonate aldolase (DAHP synthase)
<i>aldA</i>	0.48	0.07	0.55	C	aldehyde dehydrogenase A, NAD-linked
<i>cstA</i>	0.35	0.05	0.40	T	peptide transporter induced by carbon starvation
<i>aceA</i>	0.34	0.05	0.39	C	isocitrate lyase monomer
<i>cspD</i>	0.31	0.05	0.36	K	DNA replication inhibitor
<i>aceB</i>	0.27	0.04	0.31	C	malate synthase A
<i>trg</i>	0.27	0.04	0.31	N	methyl accepting chemotaxis protein – ribose/galactose/glucose sensing
<i>groL</i>	0.26	0.04	0.30	O	GroEL chaperonin, peptide-dependent ATPase, heat shock protein
<i>dnaK</i>	0.24	0.03	0.27	O	chaperone protein DnaK
<i>yfiA</i>	0.18	0.03	0.21	J	stationary phase translation inhibitor and ribosome stability factor
<i>gatC</i>	0.17	0.03	0.20	G	galactitol PTS permease - GatC subunit
<i>flgL</i>	0.16	0.02	0.19	N	flagellar biosynthesis; hook-filament junction protein
<i>flgK</i>	0.13	0.02	0.15	N	flagellar biosynthesis, hook-filament junction protein 1
<i>acs</i>	0.13	0.02	0.14	I	acetyl-CoA synthetase (AMP-forming)
<i>mdh</i>	0.12	0.02	0.14	C	malate dehydrogenase
<i>kgpP</i>	0.11	0.02	0.12	E	$\alpha$ -ketoglutarate: H <sup>+</sup> symporter
<i>fliA</i>	0.11	0.02	0.12	K	RNA polymerase, sigma 28 (sigma F) factor
<i>glnH</i>	0.10	0.02	0.12	E	glutamine ABC transporter - periplasmic binding protein
<i>yjdA</i>	0.10	0.01	0.11	n.a.	clamp-binding sister replication fork colocalization protein

<sup>†</sup>Only genes which expression was always significantly changed between STR and PFR P5 (FDR < 0.01) were selected for the calculations (core genes).

## Ongoing research

# Transferring Results:

*E. coli* HGT

# Ideal Strain for Large-Scale Application

Michalowski et al, 2017 *Metabolic Engineering*

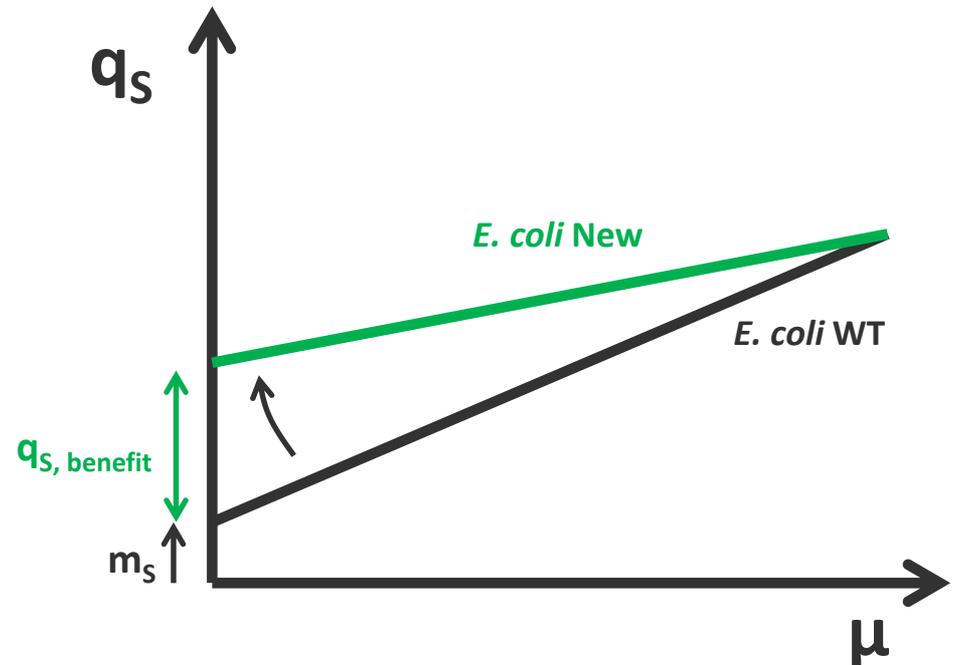
The **ideal producer** should:

- be blind with respect of extracellular heterogeneities
- enable high glucose uptake rates, even under resting condition

Goal:

to create a novel *E. coli* chassis with fundamentally changed properties.

$q_s$  is increased  
but  $m_s$  stays  
constant



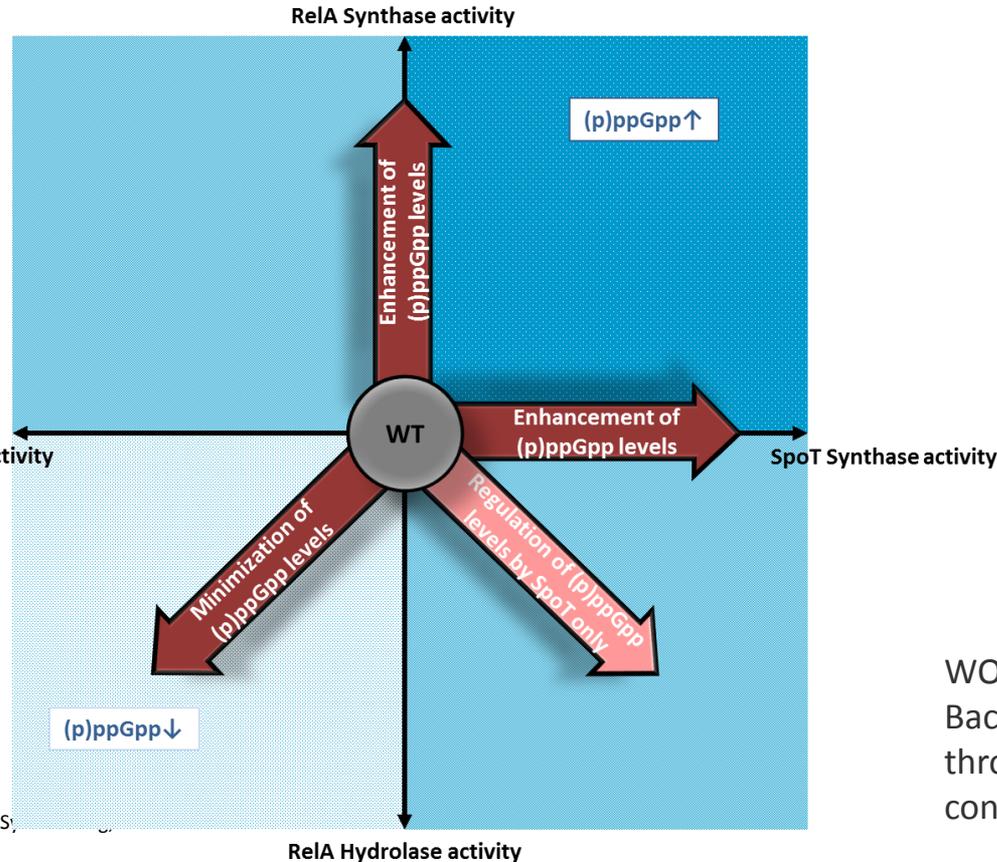
# Engineering *E. coli* HGT Following Two Guidelines

HGT = high glucose throughput

Michalowski et al, 2017 *Metabolic Engineering*

## Modulating stringent response to make *E. coli* blind

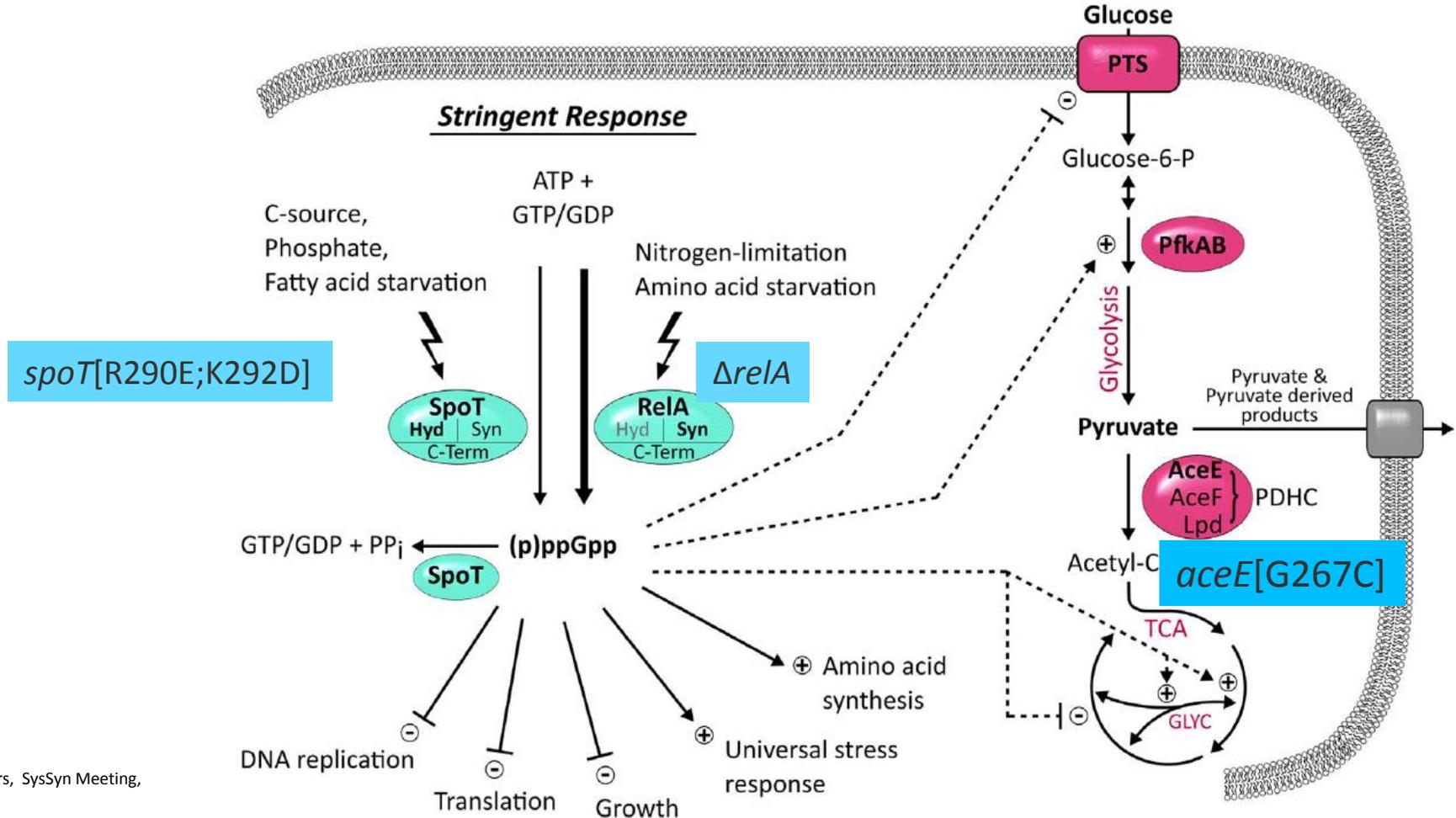
## Modulating central metabolism



Integrating *aceE\**  
(pyruvate dehydrogenase  
subunit)

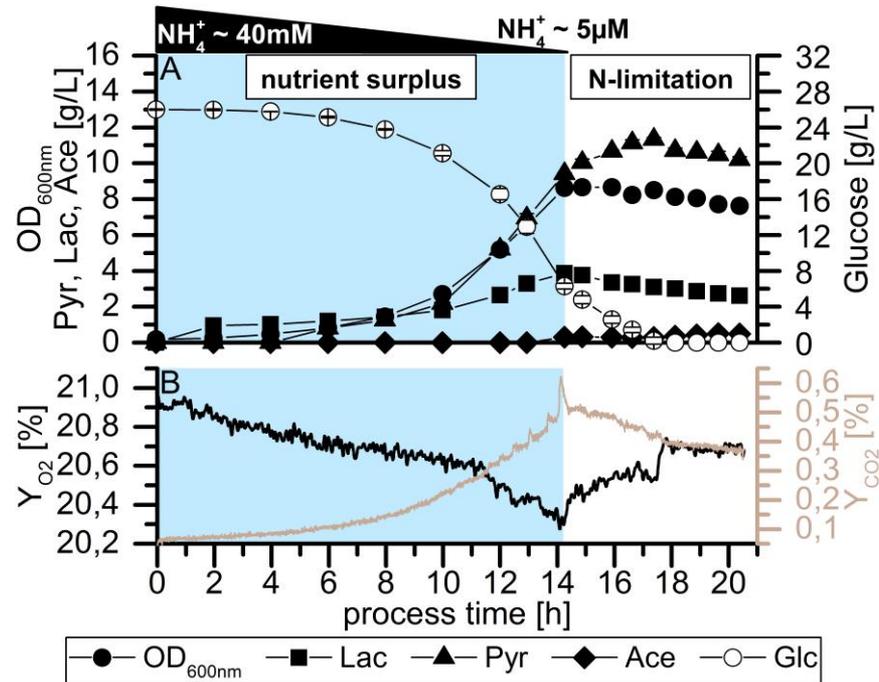
WO patent filed:

Bacterial strain and method for high throughput of sugar in the microbial conversion into biosynthetic products



# Experimental Setup

Installing ammonia limitation under glucose saturated conditions to test engineered strains



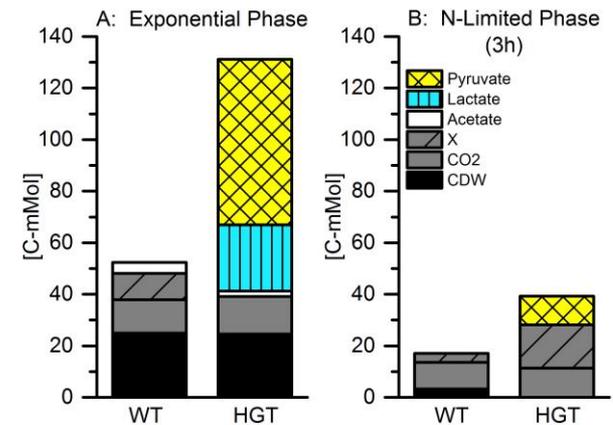
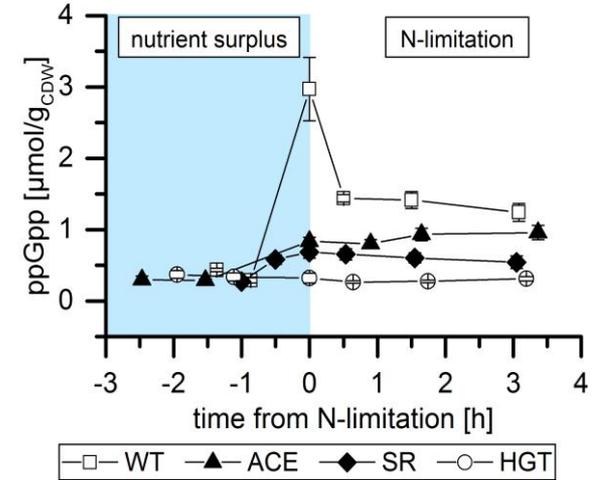
# *E. coli* HGT

Includes *aceE*\* + changes in *relA* and *spoT*

Michalowski et al, 2017 *Metabolic Engineering*

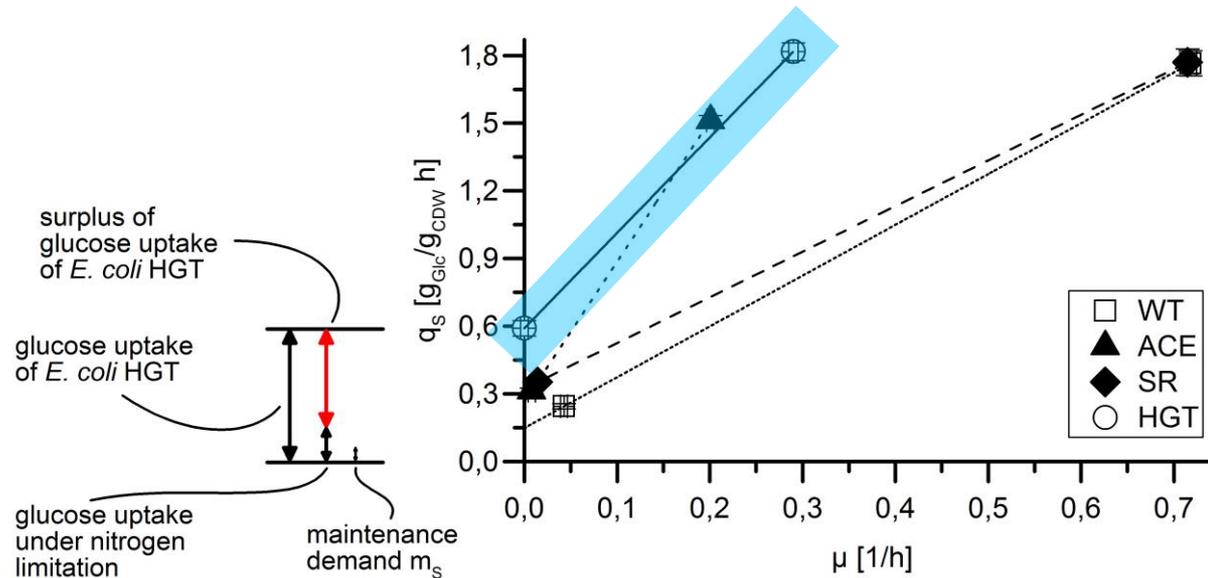
*E. coli* HGT shows no ppGpp changes under ammonia limited conditions, i.e. no stringent response initiated

*E. coli* HGT provides a surplus of pyruvate for downstream use.



# *E. coli* HGT – glucose uptake kinetics

*E. coli* HGT shows about 10 fold higher glucose uptake for non-growing conditions than needed for maintenance demands and reaches maximum uptake with 0.3 1/h. The surplus of carbon is available as pyruvate predominately.



# Summary & Thanks

- Mixing times of max 70 s should be installed preventing massive transcriptional responses
- Massive transcriptional dynamics are induced by substrate heterogeneity causing maintenance increase (1.4-1.5 fold).
- Maintenance dynamics and transcriptional adaptation can be well modelled/predicted.
- Large-scale performance can be simulated.
- Novel chassis *E. coli* HGT created.

Thanks to: **Joana Simen, Michael Löffler, Annette Michalowski, Alexander Niess**

## Thanks for Cooperation:

- IMG (AG Riess, Tübingen) for transcript measurements
- IMB (AG Sprenger) for reporter strain construction



# Different Time Scales of Response

Niess et al. .2017. *Frontiers in Microbiology*

