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# Genome-Scale *In Silico* Analysis for Enhanced Production of Succinic Acid in *Zymomonas mobilis*

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**Abstract:** Presented herein is a model-driven strategy for characterizing the production capability of expression host and subsequently identifying targets for strain improvement by resorting to network structural comparison with reference strain and *in silico* analysis of genome-scale metabolic model. The applicability of the strategy was demonstrated by exploring the capability of *Zymomonas mobilis*, as a succinic acid producer. Initially, the central metabolism of *Z. mobilis* was compared with reference producer, *Mannheimia succiniciproducens*, in order to identify gene deletion targets. It was followed by combinatorial gene deletion analysis. Remarkably, resultant *in silico* strains suggested that knocking out *pdh*, *ldh*, and *pfl* genes encoding pyruvate-consuming reactions as well as the *cl* gene leads to fifteen-fold increase in succinic acid molar yield. The current exploratory work could be a promising support to wet experiments by providing guidance for metabolic engineering strategies and lowering the number of trials and errors.

**Keywords:** *Zymomonas mobilis*; succinic acid; gene deletion; genome-scale metabolic model; systems biology

## 1. Introduction

Succinic acid (SA) is a valuable specialty chemical with a wide range of applications in food, pharmaceutical, and chemical industries, currently being synthesized through petrochemical processes by the catalytic hydrogenation of petroleum-derived maleic anhydride [1]. However, the increase in oil prices along with raising environmental awareness has made bio-based SA production an attractive option. Thus, a multitude of studies have attempted to develop SA-producing microbial fermentation systems coupled with the use of renewable biomasses [2,3]. Several well-known SA producers include *Anaerobiospirillum succiniciproducens*, *Actinobacillus succinogenes*, *Mannheimia succiniciproducens*, and recombinant *Escherichia coli*. Generally, SA is excreted during anaerobic fermentation, which has some operational disadvantages such as low cell growth and slow carbon uptake, leading to its low productivity. In addition, these producers secrete other competing fermentative byproducts, e.g., acetic acid, lactic acid, and formic acid, thus reducing SA yield and making its purification difficult.

To overcome the above limitations, researchers have tried to develop various metabolic engineering strategies to enhance SA production mostly in *E. coli* [4–8]. For example, yield was

significantly increased by amplifying the enzymatic reactions involved in SA pathway [9–11] and by introducing non-indigenous enzymes to *E. coli* [12,13]. Other interesting options are the inactivation of pathways that compete with SA [14,15] and the construction of glyoxylate cycle to enable aerobic succinate production [16–18]. For other producers, several studies were also carried out to reduce byproduct formations in *A. succiniciproducens* [19,20], *A. succinogenes* [21–23], and *M. succiniciproducens* [24,25].

In summary, various strategies described above have successfully enhanced SA yields and reduced byproduct formations. Nonetheless, there still remain issues regarding slow carbon uptake under anaerobic condition leading to low productivity. Therefore, we can consider other microorganisms that can grow well under anaerobic condition. One potential candidate is *Zymomonas mobilis* that is known to have relatively high catabolic and high glucose uptake rates, producing ethanol as the major fermentative product [26]. Moreover, Swings and DeLey [27] observed that SA was secreted in *Z. mobilis* as a minor byproduct at the yield of 0.0025–0.014 (g/g), when yeast extract was added into the medium. This evidence in conjunction with the operational advantages of anaerobic fermentation motivated us to explore metabolic engineering strategies for substantially enhancing SA production.

One strategy for improving strain performance is to identify potential targets for genetic modification. To this end, gene (or reaction) targets can be conventionally identified by random mutagenesis, followed by intelligent screening. Recently, various omics data generated by high-throughput experimental techniques have been exploited for gene identification through comparative genomic, transcriptomic, proteomic, and metabolomic studies within the context of systems biotechnology [28–32]. Apart from this high-throughput omics profiling, *in silico* analysis of genome-scale metabolic models of various microbes have been successfully employed to investigate their cellular behavior, pose new engineering hypotheses, and identify and evaluate potential genetic targets for strain improvements [33–39]. Several *in silico* analysis methods for strain optimization have been designed to select such candidates for genetic manipulations (addition and/or deletion), thereby giving rise to enhanced productivity and cellular properties. They include OptKnock [40], OptStrain [41], OptGene [42], OptForce [43], Flux-sum analysis [44], and cofactor modification analysis [45,46]. These studies have shown that genome-scale models can assist experimental studies for strain improvement [47]. In this work, we employ our previously developed genome-scale model for *Z. mobilis* and perform *in silico* analyses to explore and evaluate various strain engineering strategies to enhance SA production in *Z. mobilis*. In particular, we use constraint-based flux analyses for gene knockout simulations to develop optimization strategies for overproducing SA.

## 2. Materials and Methods

### 2.1. Genome-Scale Metabolic Model of *Z. mobilis*

The genome-scale metabolic model for *Z. mobilis* ZM4 (ATCC31821), *iZM411*, has been developed on the basis of its genome annotations [48]. This previous model was further improved using the updated information from KEGG and BioCyc, resulting in 738 reactions and 705 metabolites in 49 specific pathways or subsystems based on their functional roles. It includes major metabolic pathways, i.e., central metabolism, amino acid biosynthesis, lipid metabolism, cell wall metabolism, and vitamin and cofactor metabolism along with the necessary transport reactions for extracellular metabolites. Biomass equation is also derived from the drain of various biosynthetic precursors and relevant cofactors into *Z. mobilis* biomass at their appropriate ratios to quantify the cell specific growth rate. The complete updated model and biomass equation could be found in Supplementary 1 and 2, respectively.

### 2.2. Constraints-Based Flux Analysis

Mass balance on various metabolites under the steady state assumption gives rise to a set of linear equations with reactions fluxes as unknown quantities. It is mathematically constructed as

an underdetermined system since the number of metabolites constraints is less than the number of unknown fluxes to be determined. Thus, unknown fluxes can then be evaluated by applying linear programming to find optimum value for a given cellular objective, subjected to known uptake rates as the constraints in the model. In this study, the objective function considered was maximization of biomass growth to describe the physiological behavior under the growing condition. Various *in silico* analyses were carried out by using MetaFluxNet [49] and CPLEX 12.1.0 solver under the general algebraic modeling system (GAMS) [50].

### 2.3. Combinatorial Knockout Simulation

Combinatorial knockout analysis was performed by applying additional constraints to the current linear flux model. We removed individual reaction(s) associated with the gene(s) being knocked out from *in silico* models, and evaluated the alteration in flux distribution as the consequence of the deletion of reaction(s). For this analysis, anaerobic growth on glucose was assumed by setting glucose and oxygen uptake rates at 10 mmol/gDCW/h and zero, respectively. Biomass maximization for a steady-state metabolic network, comprised of a set  $N = \{1, \dots, n\}$  of metabolites and a set  $M = \{1, \dots, m\}$  of reactions, can be expressed in the following linear programming (LP) problem:

$$\begin{aligned} & \text{maximize } v_{\text{biomass}} \\ & \text{subject to } \sum_{j \in M} S_{ij} v_j = 0, \forall i \in N \\ & (1 - y_j) lb_j \leq v_j \leq (1 - y_j) ub_j, y_j = \{0, 1\}, \forall j \in K, K = \text{set of KO candidates} \\ & \sum_{j \in K} y_j = k, \forall j \in K, k = \text{number of genes deleted} \end{aligned}$$

where  $S_{ij}$  is the stoichiometric coefficient of metabolite  $i$  in reaction  $j$ ,  $v_j$  is flux value reaction  $j$ , and  $y_j$  is binary variable, with 1 for deleted reaction and 0 for active reaction. Gene deletion conducted in this study was for single ( $k = 1$ ), double ( $k = 2$ ), triple ( $k = 3$ ), and quadruple ( $k = 4$ ).

### 2.4. Flux-Sum Quantification

In order to quantify turnover rate of intermediate metabolites, flux-sum ( $\Phi$ ) can be defined as the summation of incoming or outgoing fluxes of given metabolite  $i$  as follows [44]:

$$\Phi_i = \sum_{j \in P_i} S_{ij} v_j = - \sum_{j \in C_i} S_{ij} v_j = \frac{1}{2} \sum_j |S_{ij} v_j|$$

where  $P_i$  and  $C_i$  denote the sets of reactions producing and consuming metabolite  $i$ , respectively. Under the pseudo-steady state assumption,  $i$  is the mass flow contributed by all of the fluxes producing (consuming) metabolite  $i$ .

## 3. Results and Discussion

The current study aimed at exploring *Z. mobilis* as potential SA producer or expression host organism and developing the *in silico* model-driven systematic strategy for strain improvement. To this end, we first evaluated the potential of *Z. mobilis* to produce SA by computing its theoretical yield using our genome-scale model. Then, we compared and contrasted the central metabolic networks of *Z. mobilis* and a known SA producer, *M. succiniciproducens*, to identify engineering targets for enhancing SA production. This network comparison allowed us to find a few target genes/reactions to be added/deleted, which were then evaluated via *in silico* analysis of the model as successfully demonstrated by Lee et al. [51]. Additionally, having narrowed down the pool of possible targets from the central metabolic reactions, combinatorial knockout analyses were carried out to obtain a list

of possible candidates for genetic modification and to investigate their KO effects on SA production. We now describe and discuss each of the above steps in detail.

### 3.1. Exploring Metabolic Capabilities for Succinic Acid Production in *Z. mobilis*

As mentioned earlier, Swings and Deley [27] experimentally observed SA yield of 0.0038–0.024 mol per mol glucose in wild-type *Z. mobilis*. Recently, Seo et al. [52] have shown the existence of *frdABCD* genes associated with succinic acid dehydrogenase which is responsible for converting fumarate to SA, from the genome sequence of *Z. mobilis*. This clearly suggests the fumarate reduction to SA is a plausible biosynthetic pathway in *Z. mobilis*. This route includes malic enzyme that converts pyruvate (PYR) to malate (MAL), which is then followed by fumarate hydratase and SA dehydrogenase. This is indeed the pathway present in *M. succiniciproducens* which is well-known succinic acid producer. Thus, our genome-scale model includes both pathways for SA production, and interestingly subsequent simulations of wild-type *Z. mobilis* on glucose confirmed that it naturally secreted SA at 0.06 molar yield during its exponential growth phase, as the byproducts in lysine and methionine biosynthesis. This yield is comparable to the yield observed by Swings and Deley [27].

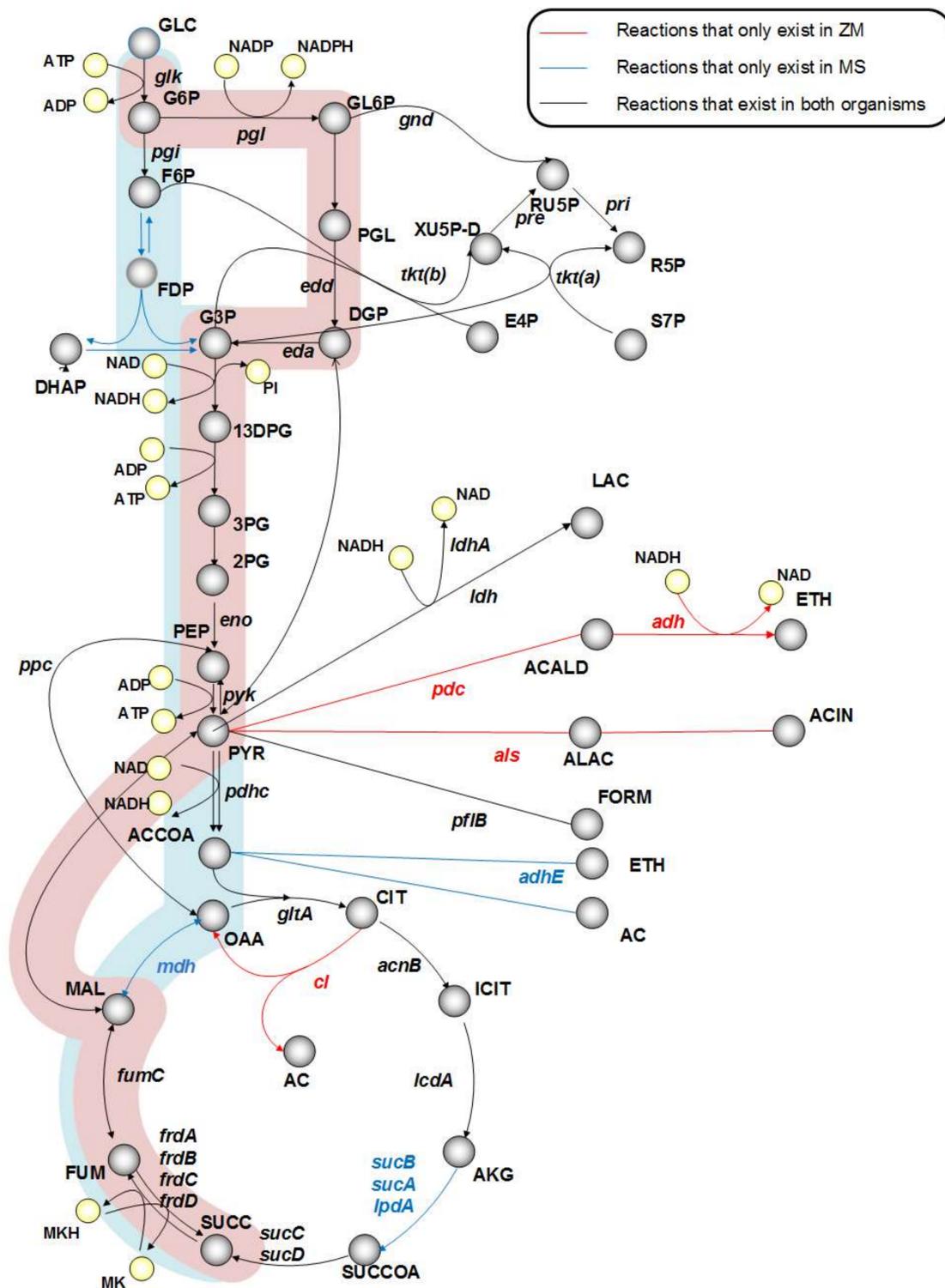
Next, we maximized SA production in our *in silico* model satisfying the required cellular growth under growing condition in the wild-type *Z. mobilis*. Simulation results showed that *Z. mobilis* was capable of theoretically producing as much as 1.6 mol SA per mol glucose. Furthermore, an increase in SA production led to a decrease in ethanol production, which clearly suggests that ethanol is a competing metabolite for SA production. To understand this SA production further, we explored how the fluxes are diverted from ethanol to SA in this scenario of maximum SA yield. Comparing the flux distribution in this scenario with the growing condition of the wild-type showed the increase in fluxes through tricarboxylic acid (TCA) cycle and carbon dioxide (CO<sub>2</sub>) uptake, while the decrease in fluxes through ethanol production pathway was observed. The attenuation of these latter fluxes is obvious again, as ethanol is a competing metabolite for SA. Interestingly, the increased uptake of CO<sub>2</sub> points to its consumption in SA production. This can be inferred from the increased flux of CO<sub>2</sub>-consuming malic enzyme that functions as the bridging reaction between glycolysis and TCA cycle in *Z. mobilis*.

### 3.2. Central Metabolism Comparison with SA Producer to Identify Gene Candidates in *Z. mobilis*

Of the several known SA producers, *M. succiniciproducens* has the highest SA yield of 1.2 mol per mol glucose, which is 60% of its theoretical SA yield [24]. Both *Z. mobilis* and *M. succiniciproducens* are anaerobic fermentative organisms without the phospho-transferring systems (PTS). Instead, they both utilize transportation protein for exchanging substrates between the cytoplasm and the surrounding environment via a process known as facilitated diffusion [14,53]. These common characteristics suggest that SA production in *Z. mobilis* can be enhanced by imitating *M. succiniciproducens*. Therefore, we compared the central metabolic pathways of *Z. mobilis* and *M. succiniciproducens* to identify gene candidates that may possibly impact fermentation profiles. One significant difference in their metabolisms is that *Z. mobilis* utilizes the Entner–Doudoroff (ED) pathway, while *M. succiniciproducens* has the Embden–Meyerhof–Parnas (EMP) pathway. Since the ED pathway in *Z. mobilis* is one major factor for its high catabolic rate, we focused more on the reactions that are uniquely present in *Z. mobilis*, but absent in *M. succiniciproducens*, which constitute potential gene deletion targets.

As illustrated in Figure 1, pyruvate decarboxylase (*pd*,  $\text{PYR} \rightarrow \text{ACALD} + \text{CO}_2$ ), acetolactate synthase (*als*,  $\text{PYR} \rightarrow \text{ALAC} + \text{CO}_2$ ), and citrate lyase (*cl*,  $\text{CIT} \rightarrow \text{AC} + \text{OAA}$ ) are three genes that are unique to *Z. mobilis*. Therefore, we created *in silico* mutants without *pd*, *als*, and *cl* to mimic *M. succiniciproducens* metabolism. The *in silico* simulation results of the wild-type strain and the knockout mutants are shown in Table 1. The deletion of *pd* increased SA production to 0.5 mol SA per mol glucose. Not surprisingly, *pd* is crucial for ethanol fermentation in *Z. mobilis*. Our simulations showed that its deletion diverts the flux from ethanol to acetic acid and SA in the TCA cycle on one hand, and the production of lactic acid and formic acid on the other. However, the deletion of

acetolactate synthase (*als*) resulted in zero growth, because this gene is essential for valine synthesis in *Z. mobilis*. Clearly, this is not a viable candidate for strain improvement.



**Figure 1.** Comparison of central metabolism in *Zymomonas mobilis* and *Mannheimia succiniciproducens*. Blue and red shadows highlight the succinic acid production pathway in *M. succiniciproducens* and *Z. mobilis*, respectively.

The deletion of citrate lyase (*cl*) did not affect SA production. But, interestingly, the deletion of *cl* in addition to that of *pdc* increased SA production further from 0.5 to 0.6 mol SA per mol glucose. While this yield is 1.1 mol lower than the maximum possible yield predicted by our *in silico* model for *Z. mobilis*, it is much higher than 0.06 mol observed for the wild-type *Z. mobilis*. This clearly shows the success of a simple approach of mimicking *M. succiniciproducens* for enhancing SA production in *Z. mobilis* as similarly reported in the previous study [9]. However, the question is whether it is possible to increase this yield even more. Therefore, we now use a combinatorial approach in the following section to identify better knockout combinations.

**Table 1.** Knockout simulations for target genes identified from central metabolism comparison.

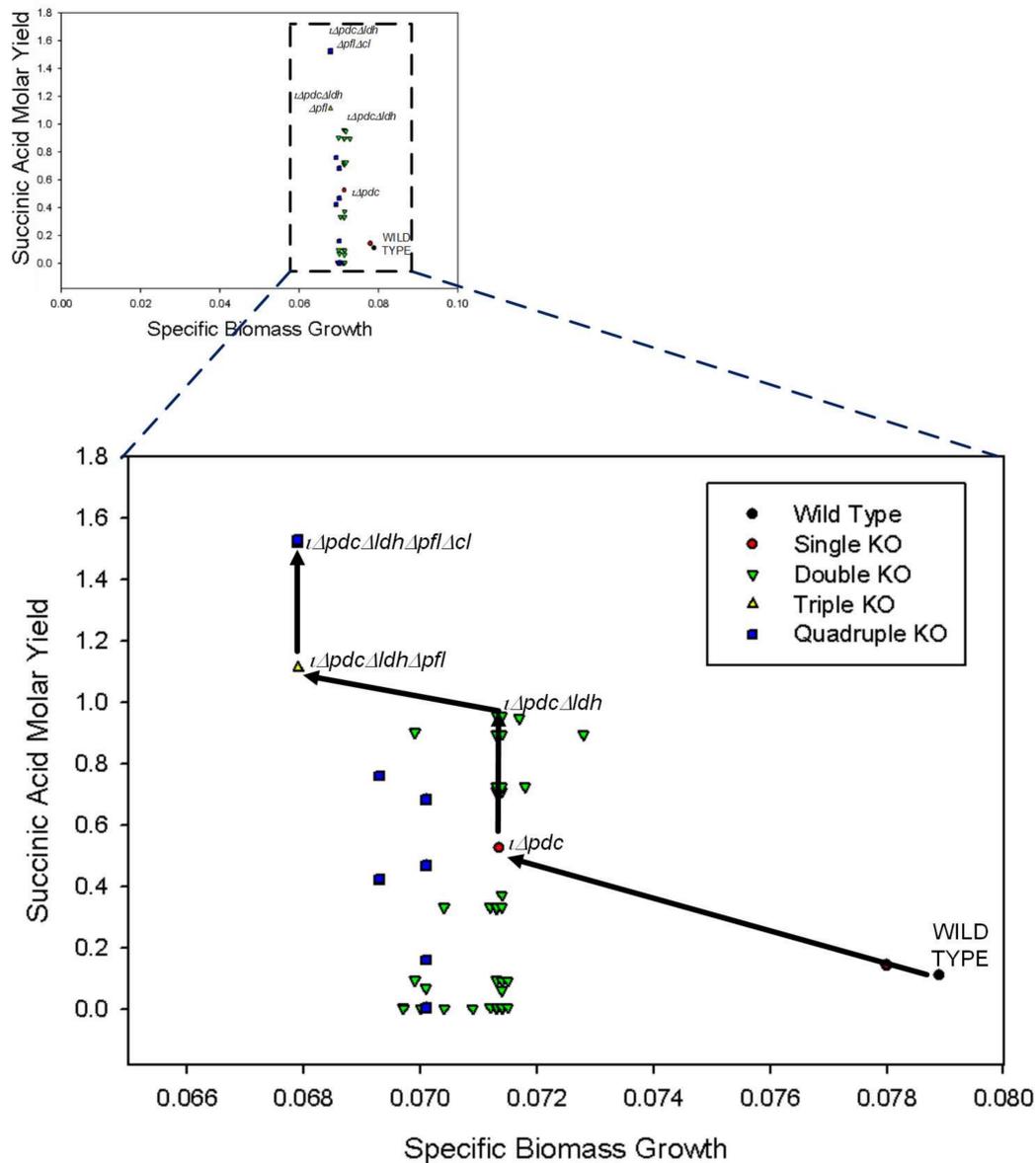
In Silico Strains	Growth Rate (1/h)	Molar Yield (mol Metabolite/mol Glucose)				
		Succinic Acid	Ethanol	Lactic Acid	Formic Acid	Acetic Acid
Wild-Type ZM4	0.08	0.06	1.76	0	0	0
<b>Metabolism Comparison</b>						
$\Delta pdc$	0.07	0.53	0	0.49	0.28	0.42
$\Delta als$	0	0	0	0	0	0
$\Delta cl$	0.08	0.06	1.76	0	0	0
$\Delta pdc\Delta cl$	0.07	0.6	0	0.71	0.28	0
<b>Combinatorial Knockout</b>						
$\Delta pdc$	0.07	0.53	0	0.49	0.28	0.42
$\Delta pdc\Delta ldh$	0.07	0.93	0	0	1.11	0.56
$\Delta pdc\Delta pfl$	0.07	0.67	0	1.12	0	0
$\Delta pdc\Delta cl$	0.07	0.6	0	0.71	0.28	0
$\Delta pdc\Delta ldh\Delta pfl$	0.07	1.14	0	0	0	0.75
$\Delta pdc\Delta pfl\Delta cl$	0.07	0.47	0	1.42	0	0
$\Delta pdc\Delta ldh\Delta cl$	0.07	1.09	0	0	1.64	0
$\Delta pdc\Delta ldh\Delta pfl\Delta cl$	0.07	1.52	0	0	0	0
<b>OptKnock/OptGene</b>						
$\Delta pdc$	0.07/0.07	0.53/0.66	0/0	0.59/0.44	0.59/0.94	0
$\Delta pdc\Delta ldh$	0.07/0.07	0.94/0.92	0/0	0.42/0.45	0/0	0.38/0.44
$\Delta pdc\Delta ldh\Delta pfl$	0.07/0.07	1.17/1.17	0/0	0/0	0/0	0.58/0.45
$\Delta pdc\Delta ldh\Delta pfl\Delta cl$	0.07/0.07	1.42/1.42	0/0	0/0	0/0	0

### 3.3. Combinatorial Knockout Analysis

It should be noted that SA is a primary metabolite of *Z. mobilis*. Therefore, our possible knockout candidates are limited to the 44 genes for the 57 reactions within the central metabolism. Out of the 44 genes, 19 are lethal genes; hence only 25 genes were considered for strain improvement. Since this number is small, we studied all possible combinations of single, double, triple, and quadruple gene knockouts. The resulting predictions are presented in Figure 2.

From single gene knockouts, we find that *pdc* is the only gene whose knockout leads to the increase in SA production at the expense of growth. Without knocking out *pdc*, it is not possible to increase SA production. However, after *pdc* is deleted, several other knockout strategies can be considered to increase SA production further. Not expectedly, cell growth is not affected at all by these additional knockouts, which is a very useful characteristic of *Z. mobilis*. From Figure 2, we see that the additional deletions of *ldh* (lactate dehydrogenase), *pfl* (pyruvate formate lyase), and *cl* all increase SA production. Of these three 2-gene knockouts, *pdc-ldh* seems to be the best for SA production with a molar yield of 0.9. Note that Lee et al. [54] had also reported *pdc* and *ldh* as KO candidates for SA production and Seo et al. [55] improved SA production by removing the genes in *Z. mobilis*. We clarified that this is only the best 2-gene knockout with a yield of 0.9 mol per mol of glucose. Further improvement is possibly achievable through 3-gene knockouts. As seen from Figure 2, *pdc-ldh-pfl* seems to be the best 3-gene knockout with an SA molar yield of 1.1 mol per mol glucose. It should be noted that disrupting

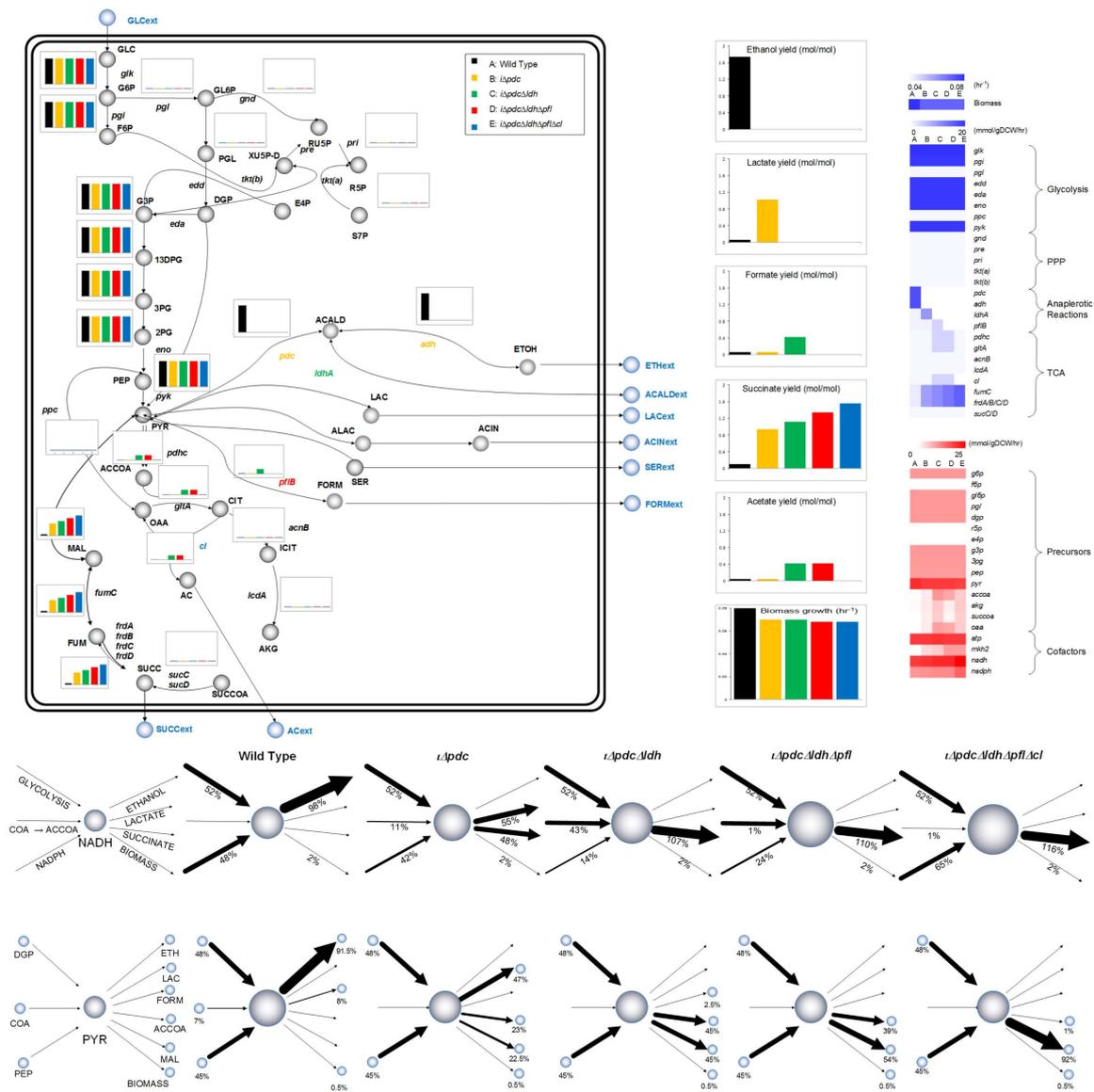
*ldh* and *pfl* genes led to the enhanced SA production in *M. succiniciproducens* and *E. coli* [24,56]. Finally, the knockout of all four genes (*pdc*–*ldh*–*pfl*–*cl*) enables us to obtain an even higher yield of 1.5 mol SA per mol glucose, which is very close to the maximum theoretical yield of 1.6 mol SA per mol glucose. Interestingly, the yield of SA was significantly increased by knockout of additional target, i.e., *cl* gene in *Aspergillus niger* [57].



**Figure 2.** Simulation results for gene knockout analysis on central metabolic pathways. The shift in biomass growth and succinic acid molar yield from wild type to quadruple knockout (KO) is shown. The best strain for SA production is also shown for single (*i* $\Delta$ *pdc*), double (*i* $\Delta$ *pdc* $\Delta$ *ldh*), triple (*i* $\Delta$ *pdc* $\Delta$ *ldh* $\Delta$ *pfl*), and quadruple (*i* $\Delta$ *pdc* $\Delta$ *ldh* $\Delta$ *pfl* $\Delta$ *cl*) knockouts.

Figure 3 illustrates the redistribution of central metabolism fluxes with sequential knockouts of *pdc*, *ldh*, *pfl*, and *cl*, explaining how the strain can be genetically engineered to increase SA production. As we can see, this 4-gene knockout diverts carbon flux entirely from ethanol to SA sequentially through lactic acid (*pdc*), formic acid (*ldh*), acetic acid (*pfl*), and finally SA (*cl*). SA production is more expensive energetically, as it requires one extra mol of NADH compared to ethanol. While ethanol production needs one mol of NADH for pyruvate conversion, SA needs one for malate formation,

and the other for menaquinone/menaquinol cycle. Figure 3 also shows how the NADH pool quantified by the flux-sum or turnover rate (see Materials and Methods) increases gradually, as ethanol is diverted to SA via lactic, formic, and acetic acids. Hong and Lee [56] have also observed in *E. coli* that higher SA production required more NADH. In contrast, ADP/ATP pool remains constant. It is also interesting to see that, while pyruvate is common to *pdc*, *ldh*, and *pfl*, only the knockout of *pdc* reduces its pool. This has a direct effect on growth, thus, the growth of *Z. mobilis* depends on the size of pyruvate pool. However, the additional knockouts of *ldh*, *pfl*, and *cl* do not affect the pyruvate pool, and hence have no effect on growth.

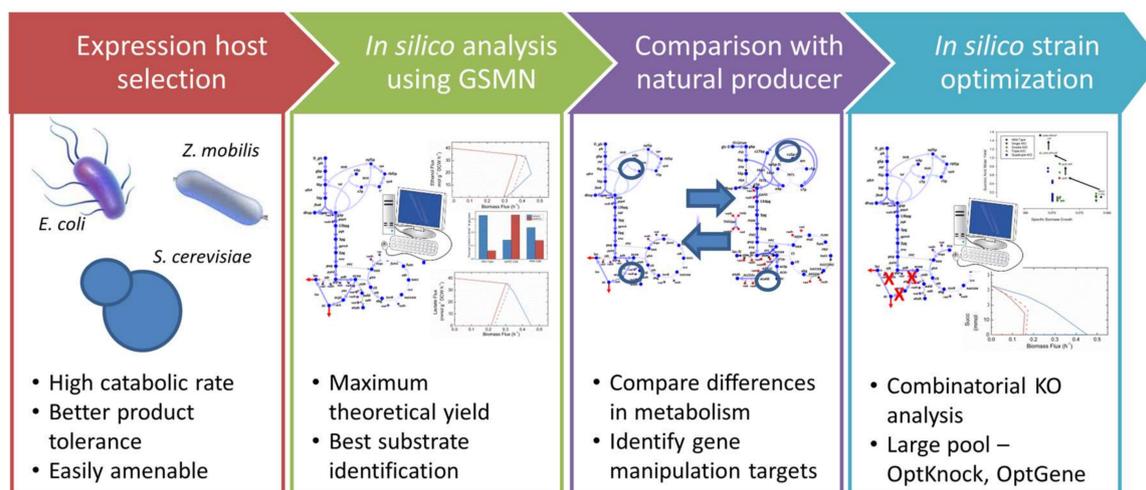


**Figure 3.** Metabolic flux distribution across the central metabolic pathways during the exponential growth phase of the microbial culture and flux-sum across the metabolite pyruvate and cofactor NADH in *Z. mobilis*. Consumption and production of the cofactor NADH and the metabolite pyruvate (PYR) is shown using the flux-sum values across each of the strains (wild type,  $\Delta pdc$ ,  $\Delta pdc \Delta ldh$ ,  $\Delta pdc \Delta ldh \Delta pfl$ ,  $\Delta pdc \Delta ldh \Delta pfl \Delta cl$ ). Percentage contribution is also shown. NADH: reduced nicotinamide adenine dinucleotide; NADPH: reduced nicotinamide adenine dinucleotide phosphate; COA: coenzyme A; ACCOA: acetyl coenzyme A; PYR: pyruvate; PEP: phosphoenolpyruvate; DGP: 2-dehydro-3-deoxy-D-gluconate 6-phosphate; MAL: malate.

### 3.4. Model-Driven Systematic Framework for Strain Optimization

Based on our analyses in the previous sections, we now propose a systematic model-driven framework for strain engineering to produce a desired target metabolite using a microbial host (Figure 4). Given a target metabolite, the first step of this framework is to select an expression host from the microbes that could potentially produce it. This expression host should have some special characteristics that would address some deficiencies such as low productivity in other expression hosts. In case of *Z. mobilis*, the high catabolic rate in anaerobic fermentation was the key feature that may offer a faster metabolite production rate. The second step is to develop and use a genome-scale model for the expression host to predict its maximum theoretical yield for the target metabolite. If the theoretical yield is comparable to those for other known producers, then the selected microbe has the potential to become a host for strain improvement.

The third step is to explore various combinations of gene modifications (deletions and/or additions) in the expression host to overproduce the target metabolite. This can be done in several ways. One way is to compare the metabolic network of the selected expression host with that of a known reference strain to identify the key differences in genes and pathways. Such a rational approach may give unique gene candidates in the reference strain and expression host for additions and deletions, respectively. The hypothesis is that the reference has optimally evolved and developed relevant synthetic pathways towards the desired metabolite [9]. In cases where only a few genes can be manipulated, as was the case in this work, this approach can be used to narrow down the pool of possible gene targets. For a small pool, it may be feasible to exhaustively consider all possible knockout combinations as done in the current study. These targets can then be evaluated using the genome-scale metabolic model to predict yields. However, for a large pool, such an exhaustive search may not be effective due to the combinatorial explosion. Therefore, another approach would be to exploit optimization techniques for strain improvement such as OptKnock [40], OptStrain [41], OptGene [42], OptForce [43], etc. While these methods may require some computational effort, some of them may guarantee the best solutions, if they converge. Both OptKnock and OptGene suggest the same strain modification as the one we have obtained in this work (Table 1). The multiple solutions of metabolites production yield observed are the results of different tools used. Note that, the SA yields obtained from different tools are almost consistent with the yields obtained from combinatorial knockout.



**Figure 4.** Proposed framework for strain improvement to overproduce a desirable target metabolite in a potential expression host (succinic acid in *Z. mobilis* in the current study).

#### 4. Conclusions

In this study, we presented a systematic approach for overproducing SA in *Z. mobilis* by using an *in silico* constraints-based flux analysis. Our genome-scale model shows that *Z. mobilis* has the capability to produce SA. Our comparison of the central metabolisms of *Z. mobilis* and the SA-producer, *M. succiniciproducens*, suggested the removal of three genes (*pdh*, *als*, and *cl*) to mimic the metabolism of the latter. The inactivation of *pdh* and *cl* increased the SA yield, but the inactivation of *als* led to zero biomass growth. However, our combinatorial gene knockout analyses pointed to the inactivation of four genes *pdh*, *ldh*, *pfl*, and *cl*, which increased yield up to 1.5 mol SA per mol glucose. This is close to the maximum possible theoretical yield of 1.7 mol SA from glucose in *Z. mobilis*. Interestingly, *pdh*, *ldh*, and *pfl* are pyruvate-consuming reactions in *Z. mobilis*, whose sequential disruption seems to redistribute pyruvate flux from ethanol to lactic acid to formic acid to acetic acid, and then finally to succinic acid homofermentatively. Based on our work, we proposed a systematic framework to overproduce a desired metabolite from an organism by using the genome-scale metabolic model. The strain engineering strategies proposed in this work can be verified in the future through wet experiments.

**Supplementary Materials:** The supplements are available online at <http://www.mdpi.com/2227-9717/6/4/30/s2>. The supplements 1 and 2 contain complete updated model and biomass equations, respectively.

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**Author Contributions:** H.W., I.A.K., and D.-Y.L. conceived and designed the *in silico* study; H.W. performed the computational simulations and drafted the manuscript; N.-R.L., and D.-Y.L. revised the paper.

**Conflicts of Interest:** The authors declare no conflict of interest.

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