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Mapping structural and environmental constraints on the mutational landscape of functional proteins using high-throughput screening and computational modeling

by Samuel Mark Thompson

DISSERTATION Submitted in partial satisfaction of the requirements for degree of DOCTOR OF PHILOSOPHY

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Mapping structural and environmental constraints on the mutational landscape of functional proteins using high-throughput screening and

computational modeling

Samuel Mark Thompson

June 9, 2020

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by

Samuel Mark Thompson

For better or for worse, my PhD has been consisted of a great deal of solitary work. This independence has been at times a challenging isolation and a disappointment, but it has also been a tremendous gift of freedom. Generous funding from the NSF and the Chuan Lyu Fellowship and the research environment created by Tanja Kortemme in our lab at UCSF have all allowed me autonomy in my project that I did not deserve. I have also been fortunate to claim time from my thesis committee members – Geeta Narlikar and David Agard – both of whom I greatly admire and who have made themselves available whenever I have asked. Beyond this, my project was also built on a great deal of previous work and and many new contributions. My computational work would not have been possible without the decades of hard-work within the Rosetta community nor without specific contributions from Noah Ollikainen, Colin Smith, Andrew Leaver-Faye, and most especially from Amelie Stein and Tianjiao Zhang. The experimental components of this project have their backbone in prior work from Kim Reynolds at UT Southwestern, who has somehow managed to be an exceptional collaborator and an accessible mentor from afar. Chris Ingle, Thuy Nguyen, and Victor Salinas from UT Southwestern have been patient and generous in providing materials and helping me troubleshoot selection and sequencing experiments via the internet. Alongside Chris, Anna Sellas, Norma Neff, and Rene Sit at the Chan-Zuckerberg BioHub, and Natasha Carli and Jim McGuire at the Gladstone Institute Genomics Core facilitated or performed all of the Illumina sequencing for my selection experiments, including several re-runs of samples that I prepared. Carol Gross's perception and insight saved my project when I did not know how to go from an intriguing observation to a true scientific discovery, and Melanie Silvis and Byoung Mo Koo from her lab provided expertise and materials that were essential to the experiments that revealed what I believe will prove to be the most important findings herein. Many of the experiments to support these findings would not have been completed in time without Sunny

Zhang's diligence and careful experimentation. In preparing the manuscript and this thesis, I am reminded of how Tanja has been instrumental in shaping how I conceptualize what comprises a novel scientific result and how I communicate science in text, in images, and in speech. Of course, I would be remiss not to dedicate the final product here to my grandfather of self-same name, as he revels in seeing his name in print.

To Steven, thank you for your patience, independence, love, support, enthusiasm, and laughter. Everything has been a richer experience with you.

This thesis was written during the shelter-in-place implemented to stem the spread of the Covid-19 pandemic and was completed during a time of protest against systemic racist violence against people of color, police violence against Black Americans in particular. It would be irresponsible not to acknowledge how privileged I have been to enjoy stable housing, continued income, and good health while isolating myself at home to write. I think I will always feel that I used my thesis deadlines as an excuse not to be more involved in combating the multiple crises that we are currently facing. That is a sobering and regretful thought.

Some text and figures in this dissertation are reprints of or modified from material as it appears in "Altered expression of a quality control protease in *E. coli* reshapes the in vivo mutational landscape of a model enzyme", *eLife*, **2020**. The co-author listed in this publication directed and supervised the research that forms the basis for this dissertation.

Mapping structural and environmental constraints on the mutational landscape of functional proteins using high-throughput screening and computational modeling

Samuel Mark Thompson

Abstract

Natural protein sequences are the result of optimization on a mutational landscape with multiple competing pressures. These pressures will arise from constraints imposed by selection for a particular fold and function within a cellular context. We can categorize these pressures as structural-functional and environmental. Nevertheless, it remains a challenge to quantify mutational landscapes with thousands of mutations and dissect the contributions from multiple constraints. Similarly, we generally do not know how to encode protein design models with the structural constraints that define a complex molecular function, even simplified *in vitro* environments. Reverse-engineering the multiple structural-functional and environmental pressures that were integrated to yield the mutational landscapes that produced natural proteins would improve our understanding of the cellular milieu and our ability to engineer new protein functions.

Using *E. coli* dihydrofolate reductase (DFHR) as a model system, we developed computation and experimental methods for identifying, quantifying, and modeling structural-functional and environmental constraints on functional proteins. **Chapter 1** of this thesis is a brief introduction to the concept of mutational landscapes and to our model enzyme. **Chapter 2** of this thesis (page 11) describes a multi-state modeling framework for encoding complex functions into protein design and the application of this framework to recovering evolutionary sequence preferences in DHFR. **Chapter 3** (page 54) describes the calibration of a high-throughput selection assay for DHFR activity and the mutational landscape for a library of all possible single point mutations to

DHFR. The final chapter (**Chapter 4**, page 132) describes the quantification of broad impacts to the DHFR mutation landscape from expression of Lon protease. The results in these three chapters show the impact of structural-functional and environmental constraints on sequence preferences from mutational landscapes. These data allow us to propose methods for engineering the behavior of entire mutational landscapes by modulating environmental constraints.

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Acronyms

aTC anhydrotetracycline.

COMETS Constrained Optimization of Multistate Energies by Tree Search.

DCA direct coupling analysis.

DEE dead-end elimination.

DHF dihydrofolate.

DHFR *E. coli* dihydrofolate reductase.

DMS deep mutational scanning.

DTT dithiothreitol.

EDTA ethylenediaminetetraacetic acid.

FACS fluorescence activated cell sorting.

FADS fluorescence activated droplet sorting.

HDX hydrogen-deuterium exchange mass spectroscopy.

IPTG isopropyl β -D-1-thiogalactopyranoside.

LTEE Long Term Evolution Experiment.

MES 2-ethanesulfonic acid.

MFPred Rosetta Mean Field Prediction.

MSA multiple sequence alignment.

MSE mean squared error.

NADH nicotinamide adenine dinucleotide (reduced).

NADPH nicotinamide adenine dinucleotide phosphate (reduced).

NMR nuclear magnetic resonance spectroscopy.

PCR polymerase chain reaction.

PDB Protein Data Bank.

PMSF phenylmethylsulfonyl fluoride.

QM quantum mechanics.

QMMM mixed quantum mechanics/molecular mechanics.

RBS ribosome binding site.

RECON Rosetta Restrained Convergence.

SL sublibrary.

THF tetrahydrofolate.

TYMS *E. coli* thymidylate synthase.

WT wild-type.

1 Introduction

The future of material science and biotechnology will lie in the control of complex molecular functions at ever broader scales with ever greater control. One of the most useful platforms for nanoscale engineering is protein. Within the central dogma of biology, proteins are the effector of the control sequence that is genomic DNA. Proteins' ability to perform complex functions such as catalysis has changed our atmosphere and shaped the surface of the planet. Thus, we have evidence of the quite literally world-changing potential within engineered proteins, but we do not fully know the limits of what proteins can accomplish or how to harness their potential.

Proteins are linear chains of amino acids. **Sequence space** is hyper-dimensional space of every possible amino acid over any length of protein. Within that vast combinatorial space are pockets where the protein sequence will adopt a 3D structure that is stable enough to be characterized. These regions of sequence space for well-folded proteins overlap with regions encoding proteins with complex function. Through the optimization process of evolution, natural proteins have explored these regions of functional protein sequence space. In 1932, Sewell Wright provided the conceptual metaphor of a **mutational landscape** or fitness landscape for understanding this process of optimization[1]. The fitness landscape is a topology over sequence space where organismal fitness is the elevation. Similarly, a mutational landscape is a topology over sequence space, but the elevation is growth rate, enzyme activity, or some other quantity that can be directly measured. **Mutational impacts** are the individual changes to the measured quantity for an arbitrary sequence relative to those for a reference point in sequence space (e.g. the wild-type (WT) sequence). This heuristic of topology predicts that protein sequences will mutate to ascend an upward fitness gradient such that highly functional sequences accumulate over time.

For the goal of protein engineering, it will be highly useful to understand **1)** what shapes the

mutational landscapes that optimize proteins and **2)** how we can build computational models that encode conceptually similar constraints on sequence space to optimize proteins for non-natural, designer purposes.

1.1 DHFR

We chose *E. coli* dihydrofolate reductase (DHFR) as a model enzyme system for computational and experimental mapping of mutational landscapes because DHFR has an established *in vivo* selection assay[2], has been extensively characterized biochemically[3–10], and has been structurally characterized with crystal structures that represent the major catalytic intermediates[11]. Furthermore, we anticipated that existing literature on DHFR would help us interpret mutational impacts to generate specific and generalizable hypotheses about complex protein function and then adapt existing protocols to test those hypotheses.

1.1.0.1 Biochemistry The native activity of DHFR is the reduction of dihydrofolate (DHF) to tetrahydrofolate (THF) via hydride transfer from an nicotinamide adenine dinucleotide phosphate (reduced) (NADPH) cofactor (**Figure 1.1**, page 3). The literature values for Michaelis-Menten kinetic parameters range from 3-7 s⁻¹ for k_{cat} , 0.15-3 μ M for $K_{M, DHF}$ and \sim 0.1 μ M for $K_{M,NADPH}$ [3, 4, 12, 13]. DHF is typically the limiting reagent in *in vitro* assays for DHFR activity due to the low cellular concentration of DHF relative to $K_{M, DHF}$. While DHFR turnover is 2-3 orders of magnitude lower than the diffusion limit and DHFR's kinetic parameters are comparable to the average for all measured enzymes [14, 15], the rate acceleration from DHFR is unmeasureable because the reduction of DHF by NADPH is not detected in the absence of DHFR.

The entire kinetic cycle of DHFR has been determined based on equilibrium and pre-steady

state kinetics measurements for all on- and off-rates in addition to the rate of hydride transfer[3]. The rate limiting step of the DHFR reaction is product release (12 s⁻¹), the rate of which is essentially identical to k_{cat} for the WT enzyme (7 s⁻¹), whereas the hydride transfer step is nearly 2 order of magnitude faster (220-720 s⁻¹).

1.1.0.2 3D Structure Models from X-ray crystallography[11] and mixed quantum mechanics/molecular mechanics (QMMM) modeling[17] have been generated for major intermediates in the DHFR catalytic cycle (**Figure 1.2**, page 4). The conformational state of DHFR is defined by the identity of the bound ligands and the conformation of the M20 loop that folds over the active site. Models of the high-energy transfer state come from crystal structures of DHFR in complex with the inhibitor methotrexate that are believed to have transition state-like properties. Furthermore, QMMM simulations have been performed to model this transition state with the natural ligands.

Structural analyses of DHFR have revealed key aspects that are critical for enzyme function. Detailed nuclear magnetic resonance spectroscopy (NMR) experiments have linked the ratelimiting step (product release, *kcat*) to the rate of fluctuations in the M20 loop that folds over the active site [5, 7] The fluctuations of this loop have also been reported to be allosterically coupled with the exchange of the NADPH cofactor [18, 19]. Mutations that decrease overall enzyme velocity have acted by multiple mechanisms: disrupting hydride transfer[20], inhibiting

Figure 1.1: Hydride transfer step in the DHFR catalyzed reduction of DHF to THF. On the reaction side, a dashed line connects the hydride to the C6 carbon, which is electrophilic when the N5 nitrogen is protonated.

Figure 1.2: Crystal structures of DHFR (PDB IDs: 1RX1, 3QL3, 1RX4, and 1RX5) and a mixed QMMM model of the hydride transfer step[16] represent the conformational states adopted by DHFR over the catalytic cycle. The identity of each state is defined by the identity of the bound ligands (yellow spheres with heteroatom coloring) and the conformation of the M20 loop (outlined) that folds over the active site (closed or occluded). Upper models are in the closed state, and lower models are in the occluded state. All PDBs were downloaded from the PDB_REDO[17].

the protonation of nitrogen N5 and shifting the *pK^a* of the reaction[12], eliminating hydrogen bonds stabilizing the interactions between the M20 loop and the F-G and G-H loops[8, 9], and by altering the dynamics of the F-G and G-H loops[7, 21].

1.1.0.3 Role in Metabolism The concentration of the DHF substrate in *E. coli* cells during exponential growth is in the tens of μ M, which is sufficient to saturate the WT enzyme^[22]. The NADPH cofactor exists in the cytosol at a concentration of \sim 120 μ M[23], which is far above the K_d of 0.15 μ M for NADPH[24]. The affinity of DHFR for nicotinamide adenine dinucleotide (reduced) (NADH) measured as $K_{M,NADH}$ is 334 μ M, approximately 2 orders of magnitude higher than that for NADPH[24]. This difference allows DHFR to be specific for NADPH even though the NADH concentration in the cytosol is ~100 *µ*M.

The THF product of the DHFR reaction is essential for the synthesis of thymidine from uracil and other products of folate metabolism such as serine and glycine [25]. Because DHFR is essential for cell doubling, human DHFR is an important clinical target for anti cancer drugs. Because prokaryotic DHFRs diverge structurally from eukaryotic DHFRs[16], they are also an important target for antibiotics.

Despite DHFR activity being essential, DHFR is expected to only be \sim 90[26] to \sim 400[27] copies per cell. The measurements establishing these bounds were taken under controlled growth conditions, which is expected to have a signficant impact on the expression levels. It is estimated that DHFR is buffered such that changes in expression level do not have a measureable impact on *E. coli* growth[26] for decreases in expression down to 30% and increases of up to 7-fold relative to the endogenous expression level. The activity of DHFR is tightly coupled to the activity of the downstream enzyme *E. coli* thymidylate synthase (TYMS)[25]. This is reportedly the result of system level optimization to maintain low cellular concentrations of toxic folate intermediates[25].

1.1.0.4 *In vivo* **Assay** Critical for our experiments, an *in vivo* assay that reports on DHFR activity for a panel of mutants had already been developed by our collaborator, Kim Reynolds[2], based off a *folA* (DHFR) and *thyA* (TYMS) double knock out of ER2566 strain *E. coli*^[28]. The TYMS deletion arises spontaneously after deletion of DHFR from the *E. coli* genome[29], so in the selection assay, both genes are supplemented on a pACYC-Duet plasmid. The selection pressure in the assay comes from DNA replication and folate intermediate toxicity. The *in vivo* assay had been shown to report on DHFR activity[2], and selection could be optimized by tuning the relative expression levels of DHFR and TYMS.

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2 Modeling Functional Proteins as Multi-state Ensembles for Computational Design

2.1 Introduction

A central tenet of protein biophysics is that the amino acid sequence gives rise to a 3-D structure. This was tested by Anfinsen in seminal experiments that showed that activity could be restored for denatured ribonuclease A by gradually removing the denaturant [1]. From this result, it was inferred that protein sequence was sufficient to encode the 3D structure of a protein. The inference of sequence-structure relationships has broadly held true for the past 60 years. It has also lead to the notion that an optimized sequence can be predicted for protein structures, even structures that do not exist in nature.

The field of protein design engages in the study of how to generate designer protein sequences for specific protein folds, what are the limits of designable proteins, and how can we engineer proteins to perform useful work. In this field, *de novo* protein design is a particularly challenging area that has seen great successes over the past 25 years[2–7]. Notable milestones include the design of protein folds without natural homologues[8], the design of modular helical protein architecture through parametric design[9, 10], the design of buried hydrogen-bond networks[11], the design of multi-pass transmembrane proteins[12], the modification of dynamic motions in proteins[13], guided library design[14, 15], the design of protein biosensors[16], and the design of large protein assembles and nanocages[17–19]. A continuing challenge in this area is advancing protein design beyond static structural topologies to proteins with multiple conformations, dynamic conformational changes, and complex functions.

In this chapter, we developed an approach for modeling proteins as a multi-state system of

ensembles. We demonstrate this system using a natural enzyme as a model system, and we analyze the computational efficiency and performance of our multi-state ensemble method using a sequence tolerance benchmark on our model system.

2.2 Background

Protein engineering is a broad field, and the approaches taken in a project are largely determined by the goal. For many applications, modifying an existing protein through rational design or a library selection is the only practicable approach. Dually, the goal at the outset of a protein engineering project may be curtailed by what is possible with existing protein scaffolds. Therefore, the ability to design a *de novo* proteins with designer-specific properties would open new opportunities for biomedical engineering[20–26], chemical synthesis[27–30], and nanoscale structural engineering[6, 17].

2.2.1 Computational Protein Design

Applications of computational protein design methods include the modification of existing proteins and the de novo design of new protein structures and topologies. In either case, the key input to current state-of-the-art computational protein design methods is the knowledge of the desired protein structure. The computational design method then samples combinatorial sequence space and predicts a sequence that is optimized for the desired structure based on a biophysical scorefunction.

As with predictive models in general, this approach consists of three major components: representation, sampling, and scoring. **Representation** refers to what information and what level of complexity is used in depicting the subject of the model. Depending on the scale of the model, a protein may be modeled as a field of electron density, a cloud of points representing each nucleus, a string of beads representing each residue, or a single point. Representation plays a central role in sampling and scoring by dictating the available degrees of freedom, the functional form for modeling forces, and the applicability of computational algorithms. **Sampling** refers to both the fineness and the breadth of change that is examined by the model. In sampling sequences, all amino acids may be sampled at all positions, or the model maybe restricted to one or a few amino acids at most positions. In sampling structural conformations, the model may sample movements in Cartesian space or sample torsional rotations. Similarly, specific regions may be allowed finer sampling of conformational space (e.g. functionally important residues) and other regions (e.g. the protein backbone) may be assigned a fixed conformation. **Scoring** refers to how the model evaluates the optimality of the current solution. For protein design, a scorefunction is used as an indicator for sequences that will successfully fold into the desired conformation. Terms in the scorefunction may be drawn from statistical data or equations in the form of first principles. Scorefunctions are generally parameterized to recapitulate experimental data from biophysical experiments and quantum mechanics (QM) modeling of molecular systems. Ultimately, the desired functional properties of the real world protein must be encoded into the model on the basis of the input structural representation, sampling algorithm, and scorefunction.

2.2.2 Single-state, Ensemble, Multi-state Design Models

One promising approach for encoding complex function into computational protein models is to change the representation to make models more realistic and capture more properties of known proteins. Because we know that natural proteins undergo conformational changes that are required for function, computational models might be improved by using representations that incorporate multiple conformations. The re-design of natural proteins can also serve as a useful

test for computational methodologies, both in simulations and in wet-lab experiments.

2.2.2.1 Design Model Categories The current state-of-the-art computational design is a bespoke process, with each protocol tailored to the project. Thus, there have been many varied and inventive approaches to adding information into computational design models. For the purpose of discussing the representation of protein conformations in simulation, we will group computational design protocols into three general categories: single-state, ensemble, and multi-state design (**Figure 2.1**, page 15). Each of these approaches comes with important differences in how they approach representation, sampling, and scoring.

2.2.3 Single-state Design Models

Single-state design is arguably the current state-of-the-art. It has been used in the design of a wide range of *de novo* protein topologies[8, 19], *de novo* catalytic proteins[29], nanomolar affinity small molecule binding domains[31], and higher order protein assemblies[17, 18, 32]. Relative to models with more complex representation, single-state design is computationally efficient. Replicate simulations can also be run independently in a highly parallelized fashion. Generally, many outputs from replicate simulations are run through additional down-stream filtering criteria to select designs for final analysis and experimental characterization.

2.2.3.1 Representation Molecules in single-state design are typically represented as full-atom models. Every nucleus in the protein is represented as a point. Each atom is assigned one of a set of atom types (e.g. aliphatic carbon, aromatic nitrogen, etc.) that defines its atomic properties, including partial charge, hydrogen-bonding capacity, Van der Waals radius, Lennard-

Figure 2.1: Conceptual diagram and process flowchart for **A)** single-state, **B)** ensemble, and **C)** multi-state design models. Circles represent the backbone conformations used in the model. Ensembles sampling the same energy well are shown as stacked circles of uniform color. Models sampling different energy wells are shown as spaced circles that are colored uniquely. Below each diagram is a flowchart of generic steps used in each approach.

Jones potential well depth, and desolvation potential. Electrons and electron density are not explicitly represented in full-atom representation as they are in quantum mechanical simulations.

Protein backbones remain in a fixed conformation throughout single-state design. This is a feature that differentiates single-state design from other methodologies (**Figure 2.1**, page 15). The only degrees of freedom are in the side-chains, which are allowed to rotate around their chi angles. The discrete conformation of a side-chain is referred to as a rotamer. Rotamer libraries have been generated that sample the most probable rotamers based on statistics from the Protein Data Bank (PDB)[33, 34], and some design algorithms use continuous probability functions for continuous rotamer sampling[35, 36].

2.2.3.2 Sampling Sampling in single-state design is performed by changing the rotamers (sidechain conformations) that are on the backbone. This allows for sampling the space of rotamer configurations, where a configuration is a set of rotamer conformations over the entire protein. Sampling can be performed with rotamers for a fixed amino acid sequence or with a set of rotamers that include rotamers for multiple amino acids to simultaneously sample sequence space and rotamer configuration space.

Monte Carlo simulated annealing is one method that optimizes the rotamers to output low energy conformations[8, 37]. In each step of the simulated annealing algorithm, a randomly selected rotamer for a randomly selected position is trialed and evaluated by the Metropolis Criterion (**Figure 2.2**, page 17). Thereby, a change to the model is accepted if it lowers the model energy, but moves that increases the model energy are accepted with a probability that is dependent on the change in energy (ΔE) multiplied by a temperature factor (kT) . During the course of the simulation, the temperature factor is modulated such that the simulation is able to sample unfavorable moves at high temperatures and settle in a low energy well as the

Figure 2.2: Application of the Metropolis criterion to simulated annealing. The probability (equation, top) of accepting (green) or rejecting (red) a Monte Carlo move (e.g. rotamer substitution) is shown as a function of the change in biophysical energy after the move (ΔE) at three different temperatures (labels, right).

temperature cools. One caveat to simulated annealing is that it is not ensured to converge on the lowest energy rotamer configuration, and the output is stochastic. Convergence on a solution (e.g. rotamer configuration, sequence, or score) can only be tested by multiple repetitions of the simulation. The probability of the simulation converging on a small set of similar solutions is a function of the size of rotamer configuration space, thus at the number of design positions is limited. The maximum number of designable positions in current implementations of simulated annealing will be affected by factors such as protein topology and the number of rotamers per positions, but less than 100 positions is a reasonable limit for many applications.

In contrast, dead-end elimination (DEE) is a provable method that outputs the global minimum energy rotamer configuration[38, 39]. While the importance of the global minimum energy rotamer configuration depends on the appropriateness of the model, identifying the global minimum avoids local minima that can potentially trap a simulated annealing trajectory. One further caveat to DEE is that the simulation frequently does not converge on a solution

and no output is produced. Strategies that implement stochastic steps in sampling side-chains allow for the identification of non-optimal but low energy configurations[40], but the probability of convergence decreases as a function of the combinatorial size of rotamer configuration space, so a reasonable number of design positions in DEE is 10-20 positions with the same caveats as for simulated annealing.

2.2.3.3 Scoring A scorefunction for computational design or molecular modeling must have predictive power for what sequences and rotamer configurations will stabilize a given fold. Scorefunctions can be statistical potentials drawn from large datasets such as multiple sequence alignments [41, 42] and PDB statistics [36, 43–46]. Scorefunctions can also be explicitly parameterized to only include terms based on physical first principles [39, 47, 48]. Many scorefunctions are hybrids of the two, containing terms for both statistical physical potentials [49–51].

2.2.3.4 Optimization Single-state design is frequently followed by a minimization protocol that allows the backbone and side-chain torsion angles to adjust to the final design sequence. Many single-state design protocols now iterate between design and minimization steps such as the FastDesign protocol in the Rosetta protein design software suite. This level of backbone movement is a deviation from our definition of single-state design, but it is generally lower magnitude than that in design simulations that explicitly sample backbone movement.

2.2.4 Ensemble Design Models

In contrast to single-state models, ensemble models are not constrained to a fixed backbone. To distinguish ensemble models from multi-state models, we define an ensemble as conformations

18

that sample the same well on the energy landscape or functional conformation and that do not change the secondary structure assignment of residues.

2.2.4.1 Representation Ensemble models represent a protein with backbone flexibility. A single backbone conformation with a set of ϕ , ψ , and ω torsion angles is referred to as a conformer. Ensembles of conformers are generated by sampling the local conformers around a single input structure or by using multiple conformers from ensemble structural refinement methods. Sampling algorithms for generating backbone ensembles include Rosetta Backrub[52–54], KIC[55–57] PertMin[58, 59], or molecular dynamics trajectories[47, 50].

2.2.4.2 Sampling For each of the backbone conformers in the ensemble model, the rotamer configuration is optimized using the same algorithms as are used in single-state design. When the sequence space being sampled is very large the only output may be predictions of amino acid preferences [60, 61]. When the ensemble predictions are being compared to specific stability measurements for point mutants, the model is used to enumerate over that limited sequence space [59, 62].

2.2.4.3 Scoring Conformers and Ensembles After performing design on all members of the ensemble, aggregate properties can be extracted. If the sequence for each conformer is optimized independently, then statistics can be collected to model the amino acid preferences at each position[60, 63]. For design, individual conformers with their optimized sequences and rotamer configurations can be examined more carefully and experimentally characterized[16, 64]. In cases involving an enumerated sequence space, the energy values over the ensemble can be averaged together for each sequence. Boltzmann-weighted averaging (**Equation 2.1**, page 20) is frequently used in this step even though the sampling of conformational space in the ensemble is not sufficient to represent even the low energy microstates in the partition function. Rather, Boltzmann averaging effectively filters out the contribution to the average for a sequence from conformers that are significantly higher in energy than the median energy with a given sequence over the conformer ensemble.

$$
E_{state} = \frac{\sum_{i}^{n} E_{i} \cdot e^{(-E_{i}/kT)}}{\sum_{i}^{n} e^{(-E_{i}/kT)}} \quad for \ each \ i \ conformer \ in \ ensemble \ of \ size \ n \tag{2.1}
$$

2.2.4.4 Optimization As with single-state design, the members of the ensemble may be minimized after rotamer sampling. This step has been demonstrated to decrease error in predictions of experimental data[59, 62].

2.2.4.5 Hybrid Models Alternative methods have been developed that sample combined Monte Carlo moves of backbone conformations with sequence and rotamer substitutions[57, 65]. These methods may have a role in future multi-state design methodologies, particularly for small sequence spaces where ensemble generation and minimization steps may be inefficient relative to the output.

2.2.5 Multi-state Design Models

We define multi-state models as having a framework to represent a macromolecular system with a group of functionally distinct conformations or states. We note that some definitions of multistate models require the inclusion of negative states (off-target interactions or unfolded states). Under these definitions, a model that only includes positive states is a multi-constraint model. We chose to use the term multi-state here because we examine models that have the mathematical capacity to include negative states. The inclusion of negative states is not explicitly addressed here.

2.2.5.1 Representation In a multi-state model, a protein is represented as a group of states. While ensemble models represent a protein with conformers from the same well on the energy landscape, states in a multi-state model are conformers from different wells. States are frequently conformations that can be characterized individually by structural methodologies such as x-ray crystallography and NMR spectroscopy. The structural difference between states may constitute a fold change, a change in small molecule binding, a protein-protein complex interaction, or loop motions that sample multiple separate low energy conformations.

2.2.5.2 Sampling Rotamer Configuration and Scoring Individual States Rotamer optimization and scoring forms an internal loop in the multi-state design algorithm (**Figure 2.1C**, page 15). Optimization of rotamer configuration is performed using the same algorithms used in single-state design, except that the sequence is not optimized simultaneous to the rotamer configuration. As with ensemble design applied to enumerated sequence spaces, sequences on each individual state are evaluated by their score with an optimized rotamer configuration. Because each change to the sequence is followed by rotamer optimization for that sequence on all states, full atom minimization is not practical in many cases.

2.2.5.3 Sampling Sequences The external loop in multi-state design is an algorithm for sampling changes to sequences. Many algorithms have been employed, including random Monte Carlo sampling [66] and genetic algorithms[67–69] that both sample randomly and merge successful random moves. Sampling of sequence space is typically slow. For runtimes of 1 week or less, the probability that repeated simulations will converge on similar optimal sequences decreases as a function of the number of design positions and the number of states, and the maximum for systems with only 2 states is \sim 25-30 designable positions.

Figure 2.3: Fitness for each state is modeled by a sigmoidal function. Fitness (blue line) is a function of the biophysical energy of the state. The sigmoid has three regimes (labels, top) based on the overall fitness of the state and how responsive the fitness is to changes in the biophysical energy as a result of mutation.

2.2.5.4 Objective Function for Design Each sequence that is sampled must be evaluated, and design moves in sequence space must be accepted or rejected. Monte Carlo sampling utilizes the Metropolis criterion and genetic algorithms propagate a population by carrying a high scoring fraction of sequences from the current round of sampling to the next. In both cases, the scores must be integrated from all states into an objective function or fitness function that is optimized over the sampled sequence space. Many simulations use the straightforward mean energy of all states, but this method can yield poorly optimized outputs if contributions from one state dominate the other states. Furthermore, this approach does not take into account the observation that the states in a functional protein (e.g. an enzyme bound to the transition state of the chemical reaction step or and enzyme bound to the reaction products) will need to be differentially stabilized.

Warszawski et al. developed an objective function for multi-state computational design that used a sigmoidal fitness model. Scores for each state (*Estate*) were converted to a fitness score representing the predicted probability that the trial sequence stabilizes the state (**Equation 2.2**, page 23). Because the sigmoid functional form for each state have a responsive regime surrounded by two regimes where fitness is not responsive to changes in energy, compromise is possible between low-fitness and high-fitness states even if all states can significantly improve in energy

Figure 2.4: Two user-set parameters modulate the sigmoid fitness function. **A**) The offset parameter (*o*) sets the center of the fitness curve on the energy axis. **B)** The steepness parameter (*s*) sets the rate of change along the fitness curve.

(Figure 2.3, page 22). A user-defined offset parameter (o) determines the midpoint, and a steepness parameter (s) modulates the magnitude of the fitness differential with respect to energy (Figure 2.4, page 23). Effectively, the offset is an energy normalization factor and the steepness term is an inverse temperature factor. Ultimately, the total fitness for the multistate system is calculated as the joint probability of fitness over all states (**Equation 2.4**, page 23).

$$
fitness_{state} = f = \frac{1}{1 + e^{s(E_{state} - o)}}\tag{2.2}
$$

$$
fitness_{total} = F = \Pi_j^m f_j = \Pi_j^m \frac{1}{1 + e^{s(E_{j,state} - o)}} \quad for \ each \ j \ state \tag{2.3}
$$

2.2.5.5 Alternate Approaches The Constrained Optimization of Multistate Energies by Tree Search (COMETS) algorithm was developed to identify provably optimal sequences for a multistate simulation using a tree search algorithm [70]. As with other provable optimization methods like dead-end elimination, COMETS slows relative to stochastic methods as the number of design positions increases. Alternative approaches have focused on increasing the performance of multi-state design with algorithms that trade exactness for efficiency.

The CLEVER algorithm uses a cluster expansion method that fits arbitrary functions to

recapitulate the energies from single state design for a training set of sequences[37, 71]. The resulting scorefunction predictions can then be used to rapidly sample sequence space without requiring time intensive rotamer optimization. This algorithm was used to design heterodimeric coiled coils that bind with high specificity as well as affinity [72] where the average error in scorefunction energy prediction is 1-2 units. These units are approximated as kcal/mol based on correlation with experimental measurements of $\Delta\Delta G_{mutation}$, so the error in the scorefuction predictions from CLEVER is still within a regime that is usable with computational design. For other protein topologies, the CLEVER cluster expansion results in errors of 5-30 energy units.

Rosetta Mean Field Prediction (MFPred) uses a mean-field approach to estimate sequence preferences[61]. The mean field approach does not perform rotamer optimization, but it performs iterative calculations of probability-weighted averaging of all two-body energies, where rotamer probabilities are calculated from the energies in the previous round. Prediction performace with MFPred was dependent on pre-minimization of the input structures, which is expected to give strong bias to the starting sequence. Nevertheless, predictions of sequence preferences from MFPred had higher sequence entropy than predictions from single-state design (**Equation 2.4**, page 24).

$$
entropy = -\sum_{ala}^{tyr} p_i Log_{20} p_i \quad for \ each \ p_i \ probability \ of \ each \ i \ amino \ acid \tag{2.4}
$$

Finally, the Rosetta Restrained Convergence (RECON) algorithm allows the sequence on each state to optimize independently and then drives states to converge, unlike multi-state approaches that enforce convergence throughout the optimization[73, 74]. During the RECON simulation, positions that converge to a single amino acid on all states are fixed, and a convergence bonus is ramped in the scorefunction over the rounds. In the final round, uncoverged positions are designed with a greedy algorithm as follows. An unconverged position is selected randomly and all sequence substitutions are sampled at that site. The best amino acid is chosen, and the position selection continues until all positions are assigned an amino acid. When RECON was applied to a small benchmark set of proteins, its performance improved over genetic algorithms for design cases of more than 30 positions, but RECON generally output predictions with very little variation over repetitions.

2.2.6 Evaluating Design Performance

There are multiple metrics for evaluating the performance of a computational design model. Native sequence recovery tests the ability of a model to recapitulate the native sequence for an input structure (e.g. PDB structure). Sequence profile similarity tests the ability of the model to predict the first-order amino acid frequencies in a large dataset such as a multiple sequence alignment (MSA) from natural sequences or amino acid preferences from a selection experiment. It can therefore be used to quantify how a model predicts the degeneracy within a family of related sequences by examining if a model accurately distinguishes conserved and functionally important residues from residues that can more freely mutate. In contrast to profile similarity, covariation metrics such as mutual information[75, 76], direct coupling analysis (DCA)[77, 78], and statistical coupling analysis (SCA)[79, 80] attempt to quantify the interactions between residues from the second-order joint probabilities in the MSA.

2.2.6.1 Caveats for Design Metrics These metrics are in general rapid and easy to implement for purely computational benchmarks, but they are also imperfect comparisons to design simulations. Design models do not accurately represent the dynamic nature of protein structures, model the free energies (ΔH and ΔS) of folded proteins, or represent complex cellular and evolutionary environments in which the proteins were optimized. These issues with model appropriateness only exacerbate the general challenge of identifying a single natural sequence from a large degenerate sequence space that encodes proteins with nearly identical structure. For example, common performance for native sequence recovery is in the range of 30-45% for state of the art methods, and even these scores are confounded by bias to the starting sequence in the initial model.

2.2.6.2 Comparison to Experimental Measurements The best test of a design is the experimental characterization of the designed protein, but this process is far slower and more costly than a computational benchmark, especially if the molecular structure is determined. For proteins with a measureable activity, methods for high-throughput screening such as deep mutational scanning[25, 81–84] and MITOMI[85, 86] open avenues for rapidly evaluating design outcomes. Additionally, methods of DNA library synthesis and screening have been developed to examine the fold stability of thousands of small miniproteins (\sim 50 aa) in a single experiment[87, 88].

Other experimental datasets can also be useful in evaluating a model. It is expected that a design algorithm that can successfully predict sequences that function and/or fold into a desired structure will also have predictive power for the biophysical impact of point mutations. When paired with protein structures, large databases of $\Delta\Delta\mathsf{G}_{folding}$ and $\Delta\Delta\mathsf{G}_{binding}$ measurements can be used to evaluate changes to representation, scoring, and sampling in a model. Estimates of \sim 0.01-0.1 kcal/mol for the non-additive error per residue have been suggested for a design model to have an total expected error of ~1 kcal/mol^[89], so improvement in $\Delta\Delta G_{folding}$ and $\Delta\Delta G_{binding}$ predictions is expected to result in improvements in the generation of functional sequences. As protein design expands into the design of protein dynamics, metrics such as the prediction of side-chain order parameters from NMR experiments[52, 90, 91] and room-temperature X-ray crystallography[92–95] are expected to be increasingly important.

2.2.7 Rosetta

The work in this chapter is performed in the Rosetta protein design suite[3, 51]. Rosetta is a state-of-the-art software package for macromolecular design. It has been used to design *de novo* protein folds[8, 9, 19], buried hydrogen-bond networks[10], orthogonal binding partners[11], small molecule binders[16, 26, 31], metalloproteins[96], catalytic proteins[30, 97–99], multipass membrane proteins[12], and higher-order protein assemblies[32]. Multiple multi-state design methods have been implemented in Rosetta, including MPI_MSD[68], RECON[73], MFPred[61], and Rosetta MSF[69].

2.2.7.1 The Rosetta Scorefunction The Rosetta scorefunction is a hybrid scorefunction of physical and statistical terms. It contains a Coulombic potential for electrostatics, a 6-12 potential for attractive and repulsive Van der Waals interactions, and a hydrogen-bonding potential. It contains statistical potentials for side-chain rotamers and backbone torsion angles. It is not polarizable, and it does not currently contain pi-pi or cation-pi interaction terms. The solvation term is a Lazaridis-Karplus implicit solvation model. The current scorefunction is REF2015 and it has been benchmarked against a series of performance and experimental tests[51].

2.2.8 Challenges for Multi-state Design

Despite the many developments for multi-state design protocols, a consistent set of challenges remains around computational efficiency because the optimization of rotamer configuration and amino acid sequence are separated into two processes. Multi-state design protocols require significantly more computational resources that independent single-state design simulations run over the same number of states. Multi-state models also restrict the number of design positions to fewer than are needed to generate a well-folded miniprotein. Therefore the practical application of multi-state design methods has been limited to the design of residues on the interface of helical bundles [72, 100, 101] and 22-23 loop residues in the loops of an antibody[23, 24], and no method has been applied to a design project that evaluates thousands of varied designs in high-throughput. It would be a notable advance if the successful design of a protein fold with *>*100 residues was computationally tractable with a multi-state method. An even greater advance would be to apply the model to the design of a protein with complex function.

2.3 Results

To advance computational protein design methodologies for functional proteins, we sought to develop a model that could encode multiple structural constraints for a functional protein, make predictions about the extent of tolerated sequence space, with sufficient computational efficiency to design a 5-20 kDa monomeric protein.

2.3.1 A Multi-state Ensemble Design Model

We chose to combine the two models types that separately accomplish each of these goals: multi-state models and flexible-backbone ensemble models (**Figure 2.5BC**, page 29). A protein is represented in the multi-state ensemble mode by macrostates of functionally required conformations (e.g. crystal structures of catalytic intermediates or of multiple binding conformations)(**Figure 2.5D**, page 29). Macrostates are represented as ensembles of flexible-backbone microstates as in ensemble design (**Chapter 2.2.4**, page 18). Energies for sequences (*Ei*) are calculated as averages over the ensemble of microstates. Fitnesses for each macrostate (f) are calculated from the macrostate energies using the sigmoidal model[66] that has been modified to add an exponential weight for each state (*k*). Finally, the total energy of

Figure 2.5: Comparison of Workflows in Multi-state Ensemble Models to Single-state, Ensemble, and Multi-state Models. Conceptual diagram and process flowchart comparing **A)** single-state, **B)** ensemble, and **C)** multi-state design models to proposed workflows for **D)** multi-state ensemble design models using enumerated energies **E)** and multi-state design with statistical energies from ensembles. Circles represent the backbone conformations used in the model. Ensembles sampling the same energy well are shown as stacked circles of uniform color. Statistical energies are reresented by the MSAs from sequence tolerance. Models sampling different energy wells are shown as spaced circles that are colored uniquely. Below each diagram is a flowchart of generic steps used in each approach.

Figure 2.6: Macrostates and microstates in a multi-state ensemble model. (Top row) Macrostates of a protein with complex function (top row) are depicted as ensembles of flexible-backbone microstates using DHFR as an example (PDB IDs: 1RX5, 3QL3, 1RX1). Energies extracted from the microstates (bottom row) and fitnesses are calculated as described in **Chapter 2.3.1** (page 28).

the system (*F*) is calculated at the product of the macrostate fitnesses, as in the orignal sigmoidal model (**Equation 2.5**, page 30). Because the fitnesses (*f* and *F*) are probability-like terms, the log of these terms is an energy-like term. Therefore, exponential weights in the fitness are scalar multipliers for each macrostate energy.

$$
fitness_{total} = F = \Pi_j^m f_j^{k_j} = \Pi_j^m \left(\frac{1}{1 + e^{s(E_{j,state} - o)}} \right)^{k_j} \quad for each j state \tag{2.5}
$$

2.3.2 Selecting a Multi-state Design Patch in DHFR

To focus our simulations on the residues that change their chemical environment during the DHFR catalytic cycle, we calculated the maximum difference in ϕ and ψ angles (**Figure 2.7**, page 31). Other metrics such as contact order change gave similar but less clear results. In contrast, the

Figure 2.7: Selection of residues for multi-state design in DHFR. **A)** Maximum cumulative change in phi and psi torsion angles for all PDB structures in Figure 1.2 (page 4). Torsion angle differences are represented on the closed (PDB ID: 3QL3) and occluded (PDB ID: 1RX5) conformations of DHFR according to the heatmap. **B)** Positions selected for multi-state design (13-24,119-123,147-149) according to maximum change in the psi and psi angles between DHFR conformations from PDB structures are colored in red on the closed conformation.

change in ϕ and ψ angles clearly highlighted residues in the highly mobile loops. We selected 20 residues in three contiguous sections (13-24, 119-123, 147-149) for multi-state design.

2.3.3 Multi-state Design on DHFR with Ensembles

To test if the multi-state ensemble model improved predictions of functional sequences in a computational design model, we tested if the model could improve predictions of sequence tolerance for DHFR relative to predictions from ensemble design on each of the individual DHFR macrostates.

2.3.3.1 Multi-state Ensemble Design on DHFR with Enumerated Sequence Energies Energies (*Ei*) were calculated for all single point mutations and used to calculate amino acid probabilities at each position (see **Methods**, **Chapter 2.5.0.1**, page 37). For the multi-state ensemble model, the global steepness parameter (*s*) and the macrostate weight parameters were optimized to best recapitulate the amino acid frequencies in the MSA of bacterial DHFR sequences from OpenSeq[103]. In comparing the computational simulations to the MSA of bacterial DHFR

Figure 2.8: Multi-state design on DHFR using energies from enumerated amino acid substitutions. Sequence profiles are shown for **A)** a multiple sequence alignment of bacterial DHFR orthologues from OpenSeq[102], **B)** multi-state design with optimized weights, and **C-G)** the individual macrostates from the DHFR structure (**Figure 1.2**, page 4) as labeled (left). For profiles form simulations, a diagram (right) indicates the state weights colors correspond to the colors in **Figure 1.2**: E-NADPH (orange), E-DHF-NADPH (red), transition state (purple), E-THF-NADPx (blue), E-THF (green).

orthologues, we observe that the simulations generally recapitulate highly conserved and highly variable positions, particularly for positions 13-24. In contrast, the predictions from the individual macrostates are either more conserved or more variable at each position compared to the MSA. Compared to the predictions from individual macrostates, the multi-state ensemble model shows improved recovery of the amino acid frequencies from the MSA better than the single macrostate models. In the optimized weights for the multi-state ensemble model, we see that the transition state is the highest weighted state followed by E-NADPH (closed conformation) and E-THF-NADPx states (occluded conformation), see **Figure 1.2** (page 4). Taken together, these results demonstrate that the inclusion of multiple functional conformations of DHFR into a design model can improve predictions of sequence tolerance.

2.3.3.2 Multi-state Design on DHFR with Statistical Energies from Ensembles The simulations from enumeration are bogged down by computational times of approximately 85 cpu hours per mutation with 200 microstates for each of 5 macrostates. Because each sequence is individually threaded onto the model, these energies do not include information about combinatorial mutations and multi-state ensemble simulations are limited by the same slow sampling of sequence space that limits most multi-state design algorithms (**Figure 2.5D**, page 29). We therefore sought to develop a computational approach that gives similar performance to multi-state ensemble design but is more computationally efficient. We developed an approach for performing multistate design using statistical energies from ensemble design – multi-state design with ensemble energies – that approximates the Rosetta scorefunction over flexible backbone ensembles for each state (**Figure 2.5E**, page 29). This multi-state design with ensemble energies method relies on simulations that are very similar to those for multi-state ensemble design excepts that all positions are designed simultaneously on each microstate rather than threading individual squences onto

Figure 2.9: Multi-state design on DHFR using first-order statistical energies from ensemble design. Sequence profiles are shown for **A)** a multiple sequence alignment of bacterial DHFR orthologues from OpenSeq[102], **B)** multi-state design with optimized weights, and **C-G)** the individual macrostates from the DHFR structure (**Figure 1.2**, page 4) as labeled (left). For profiles form simulations, a diagram (right) indicates the state weights colors correspond to the colors in **Figure 1.2**: E-NADPH (orange), E-DHF-NADPH (red), transition state (purple), E-THF-NADPx (blue), E-THF (green).

the model (see **Methods**, **Chapter 2.5.0.2**, page 38).

Simulations with multi-state design required approximately 6 cpu hours per mutation with 200 microstates for each of 5 macrostates, a 14-fold speed up over our multi-state ensemble method. Furthermore, the value of 6 cpu hours is an over-estimate because more sequence information can be extracted from the same simulations. In examining performance, we see comparable sequence tolerance predictions for energies derived from sequence enumeration and from ensemble design (**Figure 2.9**, page 34). The optimized weights show a consistent pattern with those from the simulation using enumerated energies (**Chapter 2.3.3.1**, page 31). As with the enumerated energies, the transition state is given the highest weight while one closed conformation and one occluded conformation are also highly weighted. Overall, the performance of the model for prediction of sequence tolerance from statistical energies is comparable to those from enumerated energies, but the resulting profile is more variable. These preliminary results demonstrate that using statistical energies from ensemble design is sufficient for multi-state design.

2.4 Discussion

Despite approximately 2 decades of work [100], there is still a need for computational design protocols that **1)** can include multiple structural constraints, **2)** sample alternate backbone conformations within a macrostate, and 3) are computationally efficient. Multistate design with ensemble ensemble energies has could potentially address this need because the computational cost is in the generation of the energy tables. Once the statistical energies are generated from the ensembles, the search through sequence space is dependent on a look-up table. This approach is very similar in concept to the efficient simulated annealing algorithm. This pre-generation of the energy tables for multi-state design is also performed with the CLEVER algorithm[71, 72], but inaccuracies in the approximated energies have limited the application of this method[104]. In multi-state design with ensemble energies, the computational time per sequence on DHFR would drop to \sim 1 cpu min per sequence if only 1×10^6 trial sequences are evaluated, representing a 5,000-fold increase in computational efficiency over our initial multi-state ensemble model. Rapidly sampling 1×10^8 or more sequences in this design protocol is feasible and would further improve the overall efficiency of the methodology.

2.4.1 Future Directions

The multi-state design with ensemble energies method could potentially scale favorably for the design of proteins with >100 residues because of its expected computational efficiency, although multi-state and multi-state ensemble design may be useful in simulations to refining sequences that are already close to functional regions of sequence space. In the simulations from **Chapter 2.3.3.2** (page 33), we used first order statistical energies, but is possible to extract secondorder statistical energies using direct coupling analysis (DCA) calculations[42], although larger ensembles will likely be necessary to ensure reproducibility. Further testing will determine is using enumeration to refine sequences or generating second-order statistical potentials is more efficient approach. Regardless, the multi-state design with ensemble energies methodology would benefit from additional computational testing with more natural protein systems, and the gold standard for testing the model will be the generation of functional protein sequences that have near-WT levels of activity. In addition to DHFR, enzymes such as chorismate mutase, TEM-1 betalactamase, and various proteases and nucleases could be useful test cases. The performance of the method for predicting degenerate regions of functional sequence space can be tested by sampling sequences that have a range of sequence identities compared to the sequence of the starting structural model. At the point of writing, we do not have a method for predicting the functionally required macrostates for a given function, but the computational redesign of naturally

existing proteins with complex function (e.g. catalysis) may help elucidate the constraints from function on sequence space. Ultimately, a theory that allows the *a priori* prediction of the required macrostates would allow the design of protein that performs an arbitrary function that does not exist in nature

2.5 Methods

All simulations were performed using Rosetta 3.12. Example scripts, input files, and command lines are available on https://github.com/keleayon/2020_DHFR_MSD.git.

2.5.0.1 Calculating Amino Acid Energies by Enumeration Simulations Enumerated energies for mutations were generated over flexible backbone ensembles. For each input PDB structure from the 5 states in **Figure 1.2** (page 4), an ensemble of 200 backbone conformers was generated using the Backrub application[53] with 10,000 - 15,900 trial moves evaluated by the Metropolis Criterion with $kT = 0.6$. For each backbone in each ensemble, a simulated annealing simulation was run using the FixBB application where one residue was mutated to a specific amino acid and sidechains were allowed to repack in a 10 Å shell around the designed residue, where the shell is defined as the distance between β carbons. FixBB simulations with the 5 ensembles were repeated over every possible single point mutation. For each macrostate, the microstate energies were averaged with Boltzmann weighted averaging (**Equation 2.1**, page 20) using a temperature of $kT = 2$ REU. Using the mutational energies for each macrostate, the weights for each state were optimized as described in **Chapter 2.5.0.3** (page 39). The final weights for each state were E-NADPH: 0.579, E-DHF-NADPH: 0.126, TS: 1.0, E-DHF-NADPx: 0.406, E-THF: 0.108. With these weights and energies, fitnesses were calculated for the multi-state system (**Equation 2.5**, page 30) for each mutation. A representative energy was calculated

(**Equation 2.6**, page 38) and amino acid frequencies were calculated based on a Boltzmann-weighted ensemble (**Equation 2.7**, page 38).

$$
E_{j, representative} = Ln(\frac{1}{F_j} - 1) \text{ for each } j \text{ mutation}
$$
\n(2.6)

$$
Boltzmann frequency_j = \frac{e^{s(E_{j,representative} - O)}}{\sum_{i}^{m} e^{s(E_{j,representative} - O)}} = \frac{\frac{1}{F} - 1}{\sum_{j}^{m} \frac{1}{F} - 1} \quad for \ each \ j \ mutation \quad (2.7)
$$

2.5.0.2 Calculating Amino Acid Energies from Sequence Tolerance Simulations Statistical energies for mutations were generated over flexible backbone ensembles. For each input PDB structure from the 5 states in **Figure 1.2** (page 4), an ensemble of 200 backbone conformers was generated using the Backrub application with 10,000 - 15,900 trial moves evaluated by the Metropolis Criterion with $kT = 0.6$. For each backbone in each ensemble, all positions were designed with the FixBB simulated annealing algorithm. Because DHFR is too large to design in a single simulation, design was performed using three overlapping sets of residues that ranged from 80-90 positions each. In each round of these simulations, these designed positions were allowed to sample all amino acids. In each round, positions that were not designed were allowed to repack. The output structure and sequences from one round was the input for the next round.

For each macrostate, the 200 output sequences were collected and the amino acid counts were tabulated at each position. A value of 1 was added to each count to prevent any amino acids from having a frequency of 0.0. Amino acid frequencies were calculated from the amino acid counts. Energies for each amino acid were calculated as the natural log (*Ln*) of the amino acid frequency. Using the mutational energies for each macrostate, the weights for each state were optimized as described in **Chapter 2.5.0.3** (page 39). The final weights for each state were E-NADPH: 0.0,

E-DHF-NADPH: 0.687, TS: 1.0, E-DHF-NADPx: 0.456, E-THF: 0.0. With these weights and energies, amino acid frequencies were calculated as described in **Chapter 2.5.0.1** (page 37).

2.5.0.3 Optimizing Parameters The method for optimizing parameters was developed by Tianjiao Zhang. With mutational energies for each macrostate as inputs, amino acid frequencies were calculated from fitnesses starting with random steepness and weight values. The values for these parameters were optimized using a Cuckoo-search with random Levy flights[105] to minimize the difference in frequencies in the computational predictions and in a MSA of DHFR orthologues.

$$
Objective = 1 - \sum_{i,j} | frequency_{ij,MSA} - frequency_{ij,prediction}|
$$

for each i amino acid at each j position (2.8)

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3 Deep Mutational Scanning to Resolve Highly Active Single-Point Mutants of a Model Enzyme

3.1 Introduction

A central tenet of protein biophysics is that sequence gives rise to structure which in turn gives rise to function. This understanding has largely arisen from careful examination of individual protein sequences, their structure, and their corresponding function. Further insights have been drawn from small sets of point mutations that represent small deviations from the starting sequence. New functional proteins have been engineered and evolved by capitalizing on the ability to manipulate a protein's function by manipulating a small percentage of its sequence[1].

While we know that large regions of sequence space — sparsely sampled by homologous proteins — are redundant for a particular function, single point mutations may eliminate function, enable new function, or have no impact. The challenge in distinguishing a functional protein sequence with 30% identity to a known protein and non-functional single point mutant with the same model highlights the complexity of sequence-structure-function relationships. It is a continuing challenge to identify which mutations will have a thermodynamic impact that disrupts protein fold and/or function. Accordingly, we do not know where the bounds of functional sequence space are. Mapping the mutational landscape of functional proteins under conditions that are carefully calibrated to report on a molecular function would allow us to address an elusive question about how sequence space is shaped by the thermodynamic constraints on functional proteins.

In this chapter, we sought to first accurately measure a mutational landscape for a model system, and then analyze that landscape to make inferences about how the structure and sequence

are constrained by the requirements for function. To accomplish this, we calibrated a selection assay for DHFR and screened a library of all possible single point mutants using deep mutational scanning (DMS).

3.2 Background

3.2.1 Deep Mutational Scanning

Currently, DMS is the preeminent method for measuring mutational landscapes. In DMS, mapping the mutational landscape begins with generating a library that represents the sequence space of interest. A standard library is all possible single point mutants of the target protein sequence. Selection is then performed on this library, generally in a competitive growth assay[2–5], phage display[6], or by using fluorescence activated cell sorting (FACS)[7–9] or fluorescence activated droplet sorting (FADS)[10], depending on the selectable trait.

3.2.1.1 Scientific Insights from Deep Mutational Scanning Deep mutational scanning studies have provided insights into the evolution of new protein functions [4, 7, 11], protein design [9, 12], functional trade-offs[13, 14], and adaptation to altered environments[15]. Despite these lessons, we have not learned why protein natural protein sequences are fixed, or any overarching rules that govern protein architecture and function. With a few exceptions[2, 4, 15, 16], the consistent picture from DMS studies is a general tolerance to mutation for residues outside of active sites and binding interfaces[6, 11, 13, 17, 18]. In almost all cases, it is not clear if this tolerance is the result of the specific conditions of the selection experiment or if it represents a general property of proteins. This uncertainty arises from a lack of calibration of the selection conditions in many of these experiments.

3.2.1.2 Technical Details of Deep Mutational Scanning From the DMS selection experiment, the allelic population over timepoints (for growth) or sorting gates (for FACS/FADS) is measured using standard deep sequencing. The Δ (selection population – unselected population) or linear regression slope over allele frequencies is used to calculate a selection coefficient (**Figure 3.1**, page 56). Since the initial development of the DMS methodology, it has become more common to use experimental set-ups that allow for a regression to be calculated over multiple data measurements. Because DMS libraries are often generated from degenerate codons, selection coefficients can be calculated for each allele (unique DNA sequence) or for each mutation (unique protein sequence) with averaging over redundant alleles. Given the multiple noise factors, each DMS experiment should be performed with multiple biological replicates for quantifying data quality and justifying the data analysis and interpretation.

Figure 3.1: The selection coefficient from DMS for each mutant is the slope of the linear regression of allele frequency over time. The wild-type (squares) value is normalized to zero. Advantageous (red) mutations increase and disadvantageous (blue) mutations decrease in frequency.

Timepoints The choice of timepoints has been examined as a critical factor in setting up a DMS experiment[19]. While the depth of sequencing has a negative linear relationship with the mean squared error (MSE) for selection coefficients, increasing the number of timepoints exponentially decreases the error. The experimenter should also consider the spacing of the timepoints in the experiment to better observe mutational impacts. Mutational impacts are

measurable differences in an *in vivo* or *in vitro* assay for activity, and increasing the number of timepoints early in selection will improve resolution of the strongest mutational impacts, and increasing the number of timepoints late in selection will improve the resolution of weaker mutational impacts. Furthermore, the latest timepoints will have the greatest change in signal, and some components of the noise will scale correspondingly. Thus, these points can have outsized impacts on linear regression. Having tightly spaced timepoints at the end of the experiment will decrease variation for a broad range of mutational impacts. Noise from the deep sequencer will be added to the noise from selection, and this technical noise can only be addressed by increasing the depth of sequencing or changing the sequencing platform to one with better average Q30 rates. In general, it is advisable to optimize the amount of library sequencing such that sufficient timepoints can be collected to resolve the relevant selection regime with \sim 1,000 counts per allele at each timepoint, and sequencing platforms with 4-color laser optics yield higher quality sequencing data than sequencing platforms with 2-color LED optics.

Calibration Another critical factor is calibrating the DMS selection such that the selection coefficient is an interpretable reporter. For the earliest deep mutational scanning studies, a transfer function for mapping selection coefficients to biochemical properties was not determined [6], but more recent studies have explicitly calibrated selection using mutants with known enzymatic properties [4, 7, 20] Comparing the selection coefficient to the biochemical properties of a panel of well-characterized point mutants is the gold standard for interpreting selection coefficients. While this analysis can be done after selection, identifying and characterizing a point mutant panel before performing the full selection can allow for careful calibration of the selection conditions.

3.3 Results

We began by applying DMS to map the mutational landscape of our model enzyme, DHFR (**Chapter 1.1**, page 2). Specifically, we sought to test the hypothesis that the DHFR mutational landscape is a restrictive mutational landscape constrained by multiple required functional conformations, we performed DMS over all single point mutants of DHFR.

3.3.1 Preliminary Selection on DHFR at UT Southwestern

In Kim Reynold's lab at the University of Texas, Southwestern (UTSW), we performed selection on mutations to the first 40 positions in DHFR. We made initial assumptions for several of the experiment parameters, including selection time, growth medium and supplements, temperature, minimum number of sequencing counts per timepoint (see **Methods**, **Chapter 3.5.0.7**, page 113). Only one biological replicate was performed in M9 minimal medium with 5 *µ*g/mL supplemented thymidine, and unlike the previous study[20], selection was performed for 48 hours in a turbidostat (**Figure 3.2**, page 59) to maintain culture density in early Log-phase growth (OD600 *<* 0.15). With growth rate controlled by a fixed OD600, the change in *Log*² of population frequencies over the selection timepoints can be fit to a linear model (**Figure 3.1**, page 56). Furthermore, recent results have shown that the growth rate of *E. coli* can be modulated by changing the maximum OD600, thus tuning the selection pressure (Kim Reynolds and Thuy Nguyen, correspondence). Results from this experiment using a protocol adapted from previous experiments[20] could then be used to inform a more optimized experimental protocol.

Timepoint samples from the selection experiment were analyzed by deep sequencing as described in **Methods** (**Chapter 3.5.0.7**, page 113). The median number of counts per

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Figure 3.2: A turbidostat is a continuous culture device that maintains a constant cell density.

mutant over all time points was 500 (**Figure 3.3**, page 60). The distribution of frequencies was a normal distribution over *Log*10(*counts*) and did not show a strong bias, except that the counts for the WT sequence were an order of magnitude higher than those for any other sequence. This is an expected artifact from the PCR-based construction of the library (see **Methods**, **Chapter 3.5.0.2**, page 108). We determined that the test library was of usable quality.

Selection coefficients were fit to the allele frequencies in the sequencing data (see **Methods**, **Chapter 3.5.0.7**, page 113). We observed that the Pearson correlation coefficient (R) from the fitting was not strongly correlated to the allele frequencies in the library (y-axis in **Figure 3.4**, page 61), but it was correlated with the magnitude of the selection coefficient (point size in **Figure 3.4**, page 61). Because the selection coefficient is the slope of the linear regression of $Log_2(frequency_{mutation}/frequency_{WT})$, it is expected that selection coefficients near zero will

Figure 3.3: Counts per mutant at $t=0$ during preliminary selection on positions 2-40 of DHFR.

have poor correlation coefficients even because the noise is higher than the signal. We concluded that the sequencing data was of sufficient quality, but a better method for analyzing error in the data would be needed for the final selection experiment.

To see if our selection experiment could resolve a broad range of mutational impacts, we plotted the selection coefficients in a histogram. We observed a bimodal distribution of selection coefficients with $\sim 3/4$ of the population of mutants near WT-level fitness (**Figure 3.5**, page 61). This distribution is qualitatively similar to those from previous DMS experiments[3, 4, 7, 15, 21].

To examine if biochemically intuitive patterns emerged based on the position being mutated, we plotted the selection data as a heatmap. Within the heatmap, most positions show a general tolerance to mutation. In contrast, positions that lie within the active site such as I14, G15, W22, D27, F31, and T35 are generally intolerant to mutation. Together with the distribution of all selection coefficients, we interpreted these data as indicating that the selection pressure was not sufficiently stringent to resolve highly active mutants, and mutations at conserved positions

Figure 3.4: Analysis of the error in preliminary selection coefficients. The Pearson correlation coefficient (R) value from linear regression in selection coefficient calculated is plotted against the number of initial counts for mutant. The radius of each dot is |selection coefficient|. Colors are assigned to points randomly to make points visually distinguishable.

Figure 3.5: Distribution of selection coefficients from preliminary selection experiment.

Figure 3.6: Heatmaps of selection coefficients from preliminary selection experiment. Amino acid positions (rows) are listed by the one-letter code of the WT amino acid and their position in the peptide chain. Amino acid substitutions (columns) are listed by the one-letter amino acid code. Stop codons are represented by an asterisk. Each mutant in the heatmap is colored according to its selection coefficient (colormap, right). The mutant frequencies at each timepoint are normalized to the WT frequency, so the WT sequence has a selection coefficient of 0 (see **Figure 3.1**, page 56).

with strong deleterious impacts on function will have selection coefficients that fall in the peak centered around -0.1.

To visualize the amino acid preferences at each position and examine if these preferences corresponded to a preference for the WT amino acid or amino acids that appear in DHFR orthologues, we represented the selection data as sequence profiles by calculating amino acid frequencies using the selection coefficients as energies in Boltzmann-weighted averaging (**Equation 2.1**, page 20). While the amino acid frequencies positions within the active site (15, 20, 22, 27, 31, and 35) match the amino acid frequencies for these conserved positions, the vast majority of positions do not have sequences preferences in selection that are consistent with

Figure 3.7: Amino acid preferences represented as sequence profiles for **A)** WT *E. coli* DHFR, **B)** preliminary selection, and **C)** a multiple sequence alignment of DHFR orthologues[22].

WT or orthologuous DHFR sequences. We cannot determine from these data if this is a result of very different selection pressures in nature and in our experiment, or if the difference is a result of noise in selection coefficients that are very close to WT-level under these permissive selection conditions.

3.3.1.1 Conclusions from Preliminary Selection on DHFR From this experiment, we came to several conclusions that directed the optimization of our selection experiment. First, the selection pressure in the preliminary selection experiment is permissive and needs to be increased by modifying **1)** the supplements in the growth conditions, **2)** the expression levels for the *folA* and *thyA* genes on the library construct, or **3)** the baseline growth rate of the selection strain. Second, metrics for evaluating the error in the selection experiment are limited with only one repeat experiment, and analysis of error in the regression analysis is only indicative of the precision in the measurements. To assess the accuracy of our selection coefficients, multiple biological replicates need to be performed. Third, thresholds for considering a mutant present need to be treated as a function of frequency over all counts for each timepoint to make the threshold independent of sequencing depth. Forth, the minimum number of timepoints over which a selection coefficient can be calculated should be evaluated based on how the minimum number of timepoints impacts the error between biological replicates. Finally, an average of 500 counts per timepoint was sufficient to measure large changes in allele frequency over the course of the population. The number of timepoints should be maximized while aiming for an average sequencing coverage depth of >500 counts per allele at each timepoint. We concluded that the selection pressure could be optimized using monoculture experiments with a focused panel of mutants and that issues in the data analysis could be addresses with turbidostat experiments under the optimized selection conditions.

3.3.2 Optimizing the Selection Pressure

We aimed to make DHFR activity limiting in the selection assay and increase selection pressure such that selection would resolve 2- to 3-fold changes in *kcat/K^M* relative to the WT-level DHFR value of 7.1 μ M⁻¹s⁻¹.

3.3.2.1 Identifying Highly Active DHFR Variants To test our ability to resolve near WT-level activities, we needed a panel of mutants for calibration. The original assay had been calibrated against a panel of deleterious mutants[20], so we reasoned that this calibration could be expanded to include more highly fit DHFR mutants. Previously, hyperactive variants of DHFR had been identified [23, 24], and we were able to identify 4 highly active DHFR single point mutations – L28F, L28Y, L54F, and T113V – that all have *kcat* values that are near or greater than that for WT DHFR and added them to the calibration set (**Table 3.1**, page 65).

Variant	$k_{cat} (s^{-1})$	$K_M(\mu M)$	Reference
WT.	7.95	$1.1\,$	$[20]$
W22H	1.89	18	[20]
L ₂₈ F	18.5	9.9	this work
L ₂₈ Y	19.2	21.2	this work
F31V	8.65	108	$[20]$
F31Y	20.61	80	$[20]$
M42F	79.2	13	[20]
L54F	6.3	0.7	$[25]$
L541	7.88	35	$[20]$
T113V	32.9	21.4	$[26]$
G121V	0.3	6.1	$[20]$
FI31Y/L54I	1.94	168.3	$[20]$
F31Y/G121V	0.13	90.6	$[20]$
M42F/G121V	0.4	71.8	$[20]$
L54I/G121V	0.22	73	[20]

Table 3.1: Michaelis-Menten kinetics for the set of DHFR mutants used to calibrate the selection are reported together with the reference from which the values were taken.

3.3.2.2 Comparing DHFR Selection with Two TYMS Promoters To further increase the selection pressure in our assay, we switched to a second construct generated by our collaborator, Kim Reynolds, that replaced the lac operator upstream of TYMS with a TET promoter (**Table 5.2**, page 174). We examined the relative expression levels of DHFR and TYMS in this new pTET vector (SMT201) as compared to the original pACYC vector and pACYC variant with no $His6$ tag (SMT101) . From the western-blots, we determined that ratio of TYMS expression to DHFR expression is several-fold higher in two pTET vectors (SMT201, SMT205) as compared to that in the pACYC vectors. Further competitive growth experiments performed in the plate reader under induction of TYMS with anhydrotetracycline (aTC) (see **Methods**, **Chapter 3.5.0.4**, page 110) did not change the growth rates (**Figure 3.9**, page 66), so no further optimization of TYMS expression was attempted.

Figure 3.8: Expression of FLAG-tagged DHFR and TYMS off the selection plasmid. The relative expression levels of DHFR and TYMS was observed by anti-FLAG western blot of selection plasmids with modifications to the TYMS promoter and DHFR upstream sequence. Lane identities are marked by a number (top): **1)** Ladder, **2-5)** lysates from ER2566 *folA*/*thyA* transformed with **(2)** pACYC(WT-DHFR, WT-TYMS) ()SMT101), **(3)** pACYC(his6WT-DHFR, WT-TYMS), **(4)** pTET(WT-DHFR, WT-TYMS) (SMT201), (5) pTET("AATGAG" RBS, WT-DHFR, WT-TYMS) (SMT205) see **Table 5.2**, page 174. Molecular weights to the ladder markers (labels left) and molecular identities (labels right) are indicated in label text.

Figure 3.9: Selection strain growth rate with TYMS induction off pTET plasmid. Growth rates from plate reader experiments (see **Methods**, **Chapter 3.5.0.4**, page 110) are displayed as box plots for 8 independent replicates of plate reader growth experiments using ER2566 Δ *folA*/ Δ *thyA* transformed with SMT201 (Table 5.2, page 174) expressing TYMS and either WT or W22H DHFR (**Table 3.1**, page 65). Cultures were induced with 0, 5, or 50 ng/mL aTC and grown with and without 4 hours of pre-induction (labels, bottom). An orange line marks the median. Box edges mark the first and third quartiles. Whiskers mark the maximum and minimum.

3.3.2.3 Testing Selection with a Mutated Ribosome Binding Site for DHFR To further increase selection pressure, we next sought to decrease DHFR expression. In the selection assay, DHFR is not induced. DHFR is produced through expression under glucose inhibition of the lac operon on the selection plasmid. We therefore modified the DHFR ribosome binding site (RBS) from the Shine-Dalgarno consensus sequence (AAGGAG) to "AACGAG" to reduce DHFR expression (see SMT203 in **Table 5.2**, page 174). With this construct, we performed a second preliminary selection experiment. We observed that the selection coefficients with AACGAG as the DHFR RBS (SMT203) correlated poorly both with results from our first preliminary selection (**Figure 3.10**, page 68) and with *in vitro* velocities for characterized mutants (**Figure 3.11**, page 69). We also observed that selection coefficients did not change with the addition of 0.5 μ g/mL thymidine to the selection media. From this, we concluded that selection with the SMT203 plasmid was not reporting on DHFR activity, but we were unable to determine conclusively if the poor correlation to previous experiments was a result of the "AACGAG" RBS sequence, an off-target mutation in the selection plasmid, or an unknown problem specific to this particular experiment.

3.3.2.4 Predicting Low-expression Ribosome Binding Sites for DHFR We hypothesized that we had decreased DHFR expression to a level where expression became stochastic. Therefore, our final optimization of the selection construct was to test for maximum resolution of mutant activities over a small panel of RBS strengths between the extremes of the strong "AAGGAG" (SMT201) sequence and the weak "AACGAG" (SMT203) sequence. We first calculated a predicted translation rate for "AAGGAG", "AACGAG" and 8 additional RBS sequences in the context of the upstream region of the DHFR gene in our selection plasmid (**Table 3.2**, page 70)[27, 28]. From this set, we selected two additional RBS sequences,"AAGGAA" (STM202) and "AATGAG" (SMT205), for experimental characterization of expression level and DHFR

Figure 3.10: Selection using an "AACGAG" mutated RBS sequence for DHFR yields selection coefficients that correlate poorly with preliminary selection. Selection coefficients for selection with ER2566 Δ *folA*/ Δ *thyA* transformed with SMT203 containing an RBS mutated from "AAGGAG to "AACGAG" with addition of **A)** no or **B)** 0.5 mg/mL thymide are plotted against selection coefficients from preliminary selection (see Chapter 3.3.1, page 58). Points on the scatterplot are colored by the conditions in the second round (April 2016) of selection (legend, bottom right).

mutant resolution.

3.3.2.5 Comparing WT DHFR Expression from Selection Plasmid and Endogenous Gene To determine if the mutated RBS sequences have decreased expression, we performed a western blot with anti-DHFR polyclonal antibodies, see **Methods** (**Chapter 3.5.0.11**, page 117) We observed that the selection plasmids with the "AAGGAG" (SMT201) and "AAGGAA" (SMT202) RBS sequences appear to have total DHFR expression that is greater than the endogenous expression level. The total expression level with the "AATGAG" (SMT205) and "AACGAG" (SMT203) RBS sequences appear to be much closer to the endogenous expression level. For both these mutated RBS sequences, however, DHFR expression was decreased relative to the expression from the pACYC selection plasmid used in the preliminary selection experiment (see **Chapter 3.3.1,** page 58).

Figure 3.11: Selection using an "AACGAG" mutated RBS sequence for DHFR yields selection coefficients that correlate poorly with *in vitro* kinetics. Selection coefficients for selection with ER2566 Δ *folA*/ Δ *thyA* transformed with SMT203 containing an "AACGAG" mutated RBS sequence with addition of **A)** no or **B)** 0.5 mg/mL thymidine are plotted against Log(*kcat/KM*) from *in vitro* measurements with purified enzyme. Points on the scatterplot are colored by mutant identity (legend, right). Mutants for which a selection coefficient could not be calculated are marked with an X in the plot and are assigned the lowest value.

Figure 3.12: Total DHFR expression from the optimized selection plasmid is qualitatively decreased relative to endogenous expression. The expression of DHFR was observed by anti-DHFR western blot for expression from plasmids and the endogenous gene. Lane identities are marked by a number (bottom): **1)** Ladder; **2-3)** lysates from ER2566 (2), or ER2566 Δ *folA*/ Δ *thyA* (3); 4-8) lysates from ER2566 Δ *folA*/ Δ *thyA* transformed with (4) SMT101 (pACYC, AAGGAG), **(5)** SMT201 (pTET, AAGGAG)), **(6)** SMT202 (pTET, AAGGAA, **(7)** SMT205 (pTET, AATGAG)), **(8)** SMT203 (pTET, AACGAG)) see **Table 5.2**, page 174 and **Table 3.2**, page 70. Molecular weights to the ladder markers (labels left) and molecular identities (labels right) are indicated in label text.

III DOIU ILAIICS. RBS sequence	Predicted translation rate	Construct
AAGGAG	212828.20	SMT101, SMT201
AAGGAA	66047.10	SMT202
AAAGAG	9537.00	
AATGAG	9117.30	SMT205
AAGTAG	4055.60	
AACGAG	3095.80	SMT203
AAAGAG	2959.60	
AAGTAA	2704.90	
AAGCAG	2064.80	
AAGCAA	1377.10	

Table 3.2: Predicted strength for DHFR ribosome binding sites and construct names from **Table 5.2** (page 174). Previously tested RBS (**Chapter 3.3.2.3**, page 67) sequences are in bold. RBS sequence selected for further characterization are in bold italics.

Table 3.3: Soluble expression of DHFR measured from lysate activity for heterologous expression from plasmid and for endogenous expression as described and plotted in **Figure 3.13**, page 71. Standard deviations are from three independent experiments for velocity and three biological replicates for lysate activity.

Variant	Molecules per cell	Standard deviation
WT (chromosomal)	550.0	9.2
WT (SMT102)	240.0	33.5
WT (SMT201)	330.5	17.2
WT (SMT202)	262.0	5.5
WT (SMT205)	52.0	9.2

3.3.2.6 Lysate Activity to Quantify Expression for Endogenous and Plasmid-borne WT DHFR Because the western blots for DHFR expression in the previous section (**Chapter 3.3.2.5**, page 68) were not quantitative, we next sought to quantitatively measure the soluble expression of DHFR using a lysate activity assay adapted from previous studies [29, 30]. Comparing the DHFR activity in lysates to *in vitro* velocities from purified WT DHFR (see **Methods**, **Chapter 3.5.0.14**, page 122), we were able to calculate DHFR expression. From these results, we observed that our measurement for endogenous expression of DHFR is consistent with some previous measurements of $~400$ -500 molecules/cell[31], but our measurements were higher than other previous measurements for endogenous DHFR expression in MG1566 *E. coli*[29] (**Figure 3.13**, page 71, **Table 3.3**, page 70). For the selection plasmids, soluble expression was

Figure 3.13: Soluble DHFR expression from the optimized selection plasmid is decreased relative to endogenous expression. ER2566 is the parental strain. SMT102, SMT201, SMT202, SMT205 denote plasmid constructs with altered promoters and ribosome binding sites (see **Table 5.2**, page 174). DHFR expression for plasmids was measured from DHFR activity in lysates of the selection strain, ER2566 Δ *folA*/ Δ *thyA*. Error bars represent the cumulative percent error (standard deviation) from three independent experiments for velocity and three biological replicates for lysate activity.

approximately half that of the endogenous expression level except with SMT205. This measurement for soluble DHFR expression was lower than expected base on the total apparent expression from the selection plasmids as observed on the anti-DHFR western blot (**Figure 3.12**, page 69). Nevertheless, expression decreased as expected with one mutation to the RBS. The SMT205 plasmid with an "AATGAG" RBS sequence resulted \sim 10% of the endogenous expression level (52.0*±*9.2 molecules/cell).

3.3.2.7 Plate-reader Experiment to Measure the Resolution of Selection To examine how the optimization of the selection plasmid impacted the ability of selection to resolve highly active DHFR point mutants, we generated 11 point mutations to the DHFR sequence in plasmid constructs with three RBS sequences (see **Methods**, **Chapter 3.5.0.2**, page 110). We then measured growth rates for our selection strain transformed with this plasmid panel (see **Methods**, **Chapter 3.5.0.4**, page 110). We observed linear relationship with *kcat/K^M* (**Table 3.1**, page 65) only to growth rates measured transformants of the SMT205 plasmid with an "AATGAG" RBS (**Figure 3.14(A-C)**, page 73, **Table 3.4**, page 72). From this experiment Table 3.4: Growth rates for the ER2566 Δf olA $/\Delta$ *thyA* selection strain with a panel of 12 DHFR mutants and 3 DHFR RBS sequences, see **Methods** (**Chapter 3.5.0.4**, page 110). SMT201, SMT202, SMT205 denote pTET plasmid constructs with altered ribosome binding sites (see **Table 5.2**, page 174). ND indicates that growth was not observed. NM indicates that the measurement was not taken. Standard deviations are measured over 8 independent experiments.

forward, we used the SMT205 plasmid as the optimized selection plasmid.

Because the relationship between growth rate and *kcat/K^M* was linear but poorly resolved for mutants that caused faster growth rates than did WT, we examined other kinetic properties that might better describe the observed growth phenotypes. We anticipated that some of the mutants will be saturated by the DHF substrate at cellular concentrations of low 10s of *µ*M[32], so we plotted the growth rates against DHFR reaction velocities calculated from *kcat* and *K^M* at 20 *µ*M DHF. In the plots of velocity calculated for 20 *µ*M DHF versus growth rate (**Figure 3.14(D-F)**, page 73), we observed a more consistent correlation for mutants with near-WT level velocities for the SMT205 plasmid compared to results with the other two plasmids. This demonstrated that our selection had been optimized to report linearly on a broad range of DHFR activities, including better than WT-level activities.

Figure 3.14: Correlation between *in vitro* kinetics and growth rates for DHFR point mutants shows increasing selection pressure. Growth rates for ER2566 Δf olA $/\Delta t$ hyA transformed with one of a panel of point mutants in plasmids with predicted RBS strength decreasing from left to right: SMT201, AAGGAG (**A,D**); SMT202, AAGGAA (**B,E**); SMT205, AATGAG (**C,F**), see **Table 5.2**, page 174 and **Table 3.2**, page 70. Plot points are colored by mutant identity (legend, right). Growth rates from 8 independent experiments are plotted against $\text{Log}_{10}(k_{cat}/K_M)$ (A-C) or $\text{Log}_{10}(\text{Velocity}_{10 \ \mu M \ DHF})$ (D-F).

3.3.3 Developing Non-selective Growth Conditions

With optimized and more stringent selection conditions established, we next turned to optimizing non-selective conditions for post-transformation rescue and out-growth steps. To prevent large fractions of the library population from dropping out before the first timepoint on the turbidostat, we sought to identify supplements to M9 minimal medium that would keep the growth rates of highly-fit and unfit mutants within a factor of 2. With this criterion and a WT growth rate in the range of 0.3-0.5 hr⁻¹, the relative frequency of alleles would not change by more than 10- to 20-fold between transformation and the first timepoint on the turbidostat. Additionally, because post-transformation rescue in SOB medium is necessary for sufficient transformation efficiency, we aimed for non-selective out-growth conditions in M9 medium to allow the selection strain to adapt to glucose as a carbon source. We first attempted to use a previously reported supplement mix ("*folA* mix") of 100 *µ*g/mL (1 mM) adenine, 250 *µ*g/mL (1 mM) thymidine, 1 *µ*g/mL (2 *µ*M) pantothenate, 38 *µ*g/mL (500 *µ*M) glycine, and *µ*g/mL (250 *µ*M) methionine[33]. From plate reader growth experiments with these supplements, we observed that the unfit F31Y/L54I mutant (see **Table 3.1**, page 65) had a measureable growth rate that was within 2-fold of that for WT DHFR (**Figure 3.15**, page 75), but the selection strain displayed a significant lag phase both for moderately active DHFR mutants (**Figure 3.16**, page 75) and for a monoculture of WT DHFR in the turbidostat (**Figure 3.17**, page 76). From these results, we concluded that the individual components of this published supplement should be optimized individually.

We examined the supplement components and their concentration, and hypothesized that the high concentration of nucleotides could cause toxicity by perturbing the nucleotide pools[**?**]. We therefore decreased the nucleotide concentrations, resulting in a supplement mix of 20 *µ*g/mL (75 *µ*M) adenosine, 50 *µ*g/mL (200 *µ*M) thymidine, 1 *µ*g/mL (2 *µ*M) pantothenate, 38

Figure 3.15: Selection strain growth rates in M9 minimal medium without and with the previously pubmished "*folA*" supplement mix are shown as box plots. ER2566 *folA*/*thyA* is complemented with one of 4 DHFR variants (labels bottom, **Table 3.1**, page 65) on the SMT205 optimized selection plasmid (**Table 5.2**, page 174) and grown in M9 minimal medium. For each DHFR variant, box plots represent 8 individual experiments on the plate reader (see **Methods**, **Chapter 3.5.0.4**, page 110). An orange line marks the median. Box edges mark the first and third quartiles. Whiskers mark the maximum and minimum.

Figure 3.16: Selection strain growth curves in M9 minimal medium without and with the previously published "*folA*" supplement mix. ER2566 *folA*/*thyA* is complemented with one of 4 DHFR variants (labels bottom, **Table 3.1**, page 65) on the SMT205 optimized selection plasmid (**Table 5.2**, page 174) and grown in M9 minimal medium. For each DHFR variant, growth curves are shown for 8 individual experiments on the plate reader (see **Methods**, **Chapter 3.5.0.4**, page 110).

Figure 3.17: Growth rates in the turbidostat after overnight growth in M9 minimal medium supplemented with the "*folA* mix". ER2566 *folA*/*thyA* was transformed with WT DHFR in the SMT205 selection plasmid (**Table 5.2**, page 174) and grown in M9 minimal medium under turbidostat clamp after overnight growth and 4 hours out-growth in M9 media with 100 *µ*g/mL adenine, 250 *µ*g/mL thymidine, 1 *µ*g/mL pantothenate, 38 *µ*g/mL glycine, and 38 *µ*g/mL methionine. Points represent the growth rate calculated as the linear regression slope of *Log*2(*ABS*600). Error bars represent the standard error from linear regression, and the size of the marker is scale by the Pearson R^2 value.

*µ*g/mL (500 *µ*M) glycine, and 38 *µ*g/mL (250 *µ*M) methionine. In plate reader growth experiments (see **Methods**, **Chapter 3.5.0.4**, page 110) with this supplemented M9, we observed a measurable growth rate for the F31Y/L54I mutant that was not observed in the absence of thymidine or adenosine (**Figure 3.18**, page 77). Furthermore, the growth rate with F31Y/L54I was reproducibly 60% of the growth rate with WT when using the fully supplemented M9 medium. The doubling period with WT was 1.7 hours, and the doubling period with F31Y/L54I was 2.5 hours (**Figure 3.19**, page 77). During an estimated 16-hours of rescue and overnight out-growth, the selection strain complemented with WT DHFR would go through 9.4 generations versus 6.4 generations with $F31Y/L54I$. The difference in 3 generations would result in an 8-fold change in relative frequency in the library. Finally, a monoculture of the selection strain in the turbidostat after out-growth in supplemented M9 medium did not show an initial lag phase (**Figure 3.20**, page 78). These results fulfilled our criteria for non-selective conditions.

Figure 3.18: Selection strain growth curves in supplemented M9 minimal medium without and with adenosine and thymidine drop-outs to the medium. ER2566 Δ *folA* $/\Delta$ *thyA* is complemented with one of 4 DHFR variants (labels bottom, **Table 3.1**, page 65) on the SMT205 optimized selection plasmid (**Table 5.2**, page 174) and grown in M9 minimal medium with **A)** 20 *µ*g/mL adenosine, 50 *µ*g/mL thymidine, 1 *µ*g/mL pantothenate, 38 *µ*g/mL glycine, and 38 *µ*g/mL methionine; **B)** the supplements from A) minus adenosine; or **C)** the supplements from A) minus thymidine. For each DHFR variant, growth curves are shown for 3 individual experiments on the plate reader (see **Methods**, **Chapter 3.5.0.4**, page 110).

Figure 3.19: Selection strain growth rates in M9 minimal medium. **A**) Growth rates for ER2566 Δ *folA*/ Δ *thyA* complemented with one of 4 DHFR variants (labels bottom, **Table 3.1**, page 65) on the SMT205 optimized selection plasmid (**Table 5.2**, page 174) and grown in M9 minimal medium with 20 *µ*g/mL adenosine, 50 *µ*g/mL thymidine, 1 *µ*g/mL pantothenate, 38 *µ*g/mL glycine, and 38 *µ*g/mL methionine. For each DHFR variant, box plots represent 3 individual experiments on the plate reader (see **Methods**, **Chapter 3.5.0.4**, page 110). An orange line marks the median. Box edges mark the first and third quartiles. Whiskers mark the maximum and minimum. **B)** Correlation between growth rates from A) and *in vitro* enzyme velocity at 10 *µ*M DHF calculated from Michaelis-Menten kinetics (**Table 3.1**, page 65). Plot points are colored by mutant identity (legend, right).

Figure 3.20: Growth rates in the turbidostat after overnight growth in supplemented M9 minimal medium. ER2566 *folA*/*thyA* was transformed with WT DHFR in the SMT205 selection plasmid (**Table 5.2**, page 174) and grown in M9 minimal medium under turbidostat clamp after overnight growth and 4 hours out-growth in M9 media with 20 *µ*g/mL adenosine, 50 *µ*g/mL thymidine, 1 *µ*g/mL pantothenate, 38 *µ*g/mL glycine, and 38 *µ*g/mL methionine. Points represent the growth rate calculated as the linear regression slope of $Log_2(ABS600)$. Error bars represent the standard error from linear regression, and the size of the marker is scale by the Pearson R^2 value.

3.3.4 Building a DMS Library of DHFR Single Point Mutants

We next constructed a library of all single point mutants to DHFR in our optimized SMT205 selection plasmid.

3.3.4.1 Strategy for Screening DHFR Single Point Mutants We planned the construction of our library around the technical limitations of the deep sequencing process. The DHFR gene is 477 bp, which is longer than the standard 300 bp amplicon for Illumina sequencing platforms with capacity for extended amplicon read length such as the MiSeq and the NextSeq. We considered two options to address this, 1) barcoding the library and 2) building the library as a collection of smaller sublibraries. The barcoding strategy has notable drawbacks [correspondence, Michael Schnebly and Bill Russ, University of Texas, Southwestern]. Strategies for barcoding after the library has been generated can result in additional technical noise arising from many barcodes assigned to the same allele. This effectively raises the frequency threshold that must be applied to consider a mutant present at any time point. Using library bottlenecking methods is only partially effective because low-frequency alleles will be filtered out of the library entirely while high-frequency alleles are still associated with many redundant barcodes. We determined that until libraries can be synthesized with explicit barcode-allele matching, library barcoding methods are most useful when the aim of selection is sub-sampling a much larger library sequence space. We therefore chose to pursue direct sequencing of individual sublibraries.

We chose to split the library into 4 sublibraries of mutations to no more than 40 positions each: Any 2 of these sublibraries can be pooled, screened, and sequenced together using a 300 bp amplicon. Each sublibrary was generated using the robust method of performing inverse PCR for each position in DHFR. For each position and reaction, a unique set of primers was designed and synthesized that replaced the WT codon with an NNS codon (see **Methods**, **Chapter 3.5.0.2**, page 108). All reactions were examined with agarose gel electrophoresis. If no product band was visible, the PCR reaction for that position was optimized until a visible product band appeared. Finally, reactions were pooled stoichiometrically into sublibraries by position: positions 2-40 in sublibrary (SL)1, positions 41-80 in SL2, positions 81-120 in SL3, and positions 121-159 in SL4. This yielded a version of the library that could then be subjected to quality control.

3.3.4.2 Library Quality Control To check the completeness of the library and the number of off-target mutations, we deep sequenced each of the 4 sublibraries (see **Methods**, **Chapter 3.5.0.8**, page 114, **Chapter 3.5.0.9**, page 114). Amplicons were generated for each library separately, but each amplicon covered positions in two sublibraries: SL1-SL2 or SL3-SL4. For each sublibrary, the error could be estimated from the region where no mutations are expected. We examined the background for each library as a function of the frequency-based cut-off for considering a mutation present in the library. We observed that approximately 94% of the library

Figure 3.21: Preliminary mutant frequencies in DHFR point mutant sublibraries. Mutant frequencies from deep sequencing counts for 4 sublibraries covering all single point mutants are displayed as heatmaps with a cut off of 1×10^{-4} . Rows are labeled by the position in DHFR. Columns are labeled by the amino acid identity. The matrix is split into 4 groups by sublibrary. The matrix is colored by allele frequency according to the heatmap (right).

Figure 3.22: Preliminary background frequencies in DHFR point mutant sublibraries. Background frequencies from deep sequencing counts for 4 sublibraries covering all single point mutants are displayed as heatmaps with a cut off of 1×10^{-4} . Background is assigned based on location the same amplicon reading frame. SL1 is background for SL2, SL2 for SL1, SL3 for SL4, and SL4 for SL3. Rows are labeled by the position in DHFR. Columns are labeled by the amino acid identity. The matrix is split into 4 groups by sublibrary. The matrix is colored by allele frequency according to the heatmap (right).

was covered, with missing mutations generally located at common positions (**Figure 3.21**, page 80), which is consistent with a failure at the PCR step. In contrast, the background was randomly distributed throughout the library (**Figure 3.22**, page 80), which is consistent with noise in the sequencing and mutations introduced during PCR. In the deep sequencing, we observed that mutations appeared at higher frequency in their sublibrary than they did as background mutations in another sublibrary (**Figure 3.23**, page 82). Finally, we observed that quality control from two different sequencing runs resulted in almost no overlap in background mutations. From these data, we determined that the overall quality of the library is sufficient to confirm the presence of $>90\%$ of all possible single point mutations, that the background mutations are the result of technical noise, and that deficiencies in the library could be addressed by supplementing in DNA from optimized reactions for positions that were de-enriched in the library.

We then supplemented de-enriched positions by optimizing PCR reactions for positions 2, 8, 22, 42, 43, 66, 67, 73, 74, 80, 82, 84, 89, 95, 104, 107, 118, 131, 135, 136, 140 and spiking each reaction into its respective sublibrary proportional to the total number of positions represented in the sublibrary. The supplemented library was deep sequenced and analyzed as decribed above. With the supplemented library, we observed more complete coverage over the library (**Figure 3.25**, page 83) and similar background as compared to the first round library (**Figure 3.26,** page 84), which was consistent with the expectation that background noise was due primarily to technical noise from the sequencer and from the amplicon generation process. We then calculated statistics for coverage $\frac{m}{6}$ mutations observed in library) and error $\frac{m}{6}$ mutations observed in background) in the library based on the deep sequencing (**Table 3.5**, page 85).

Figure 3.23: Comparison of mutant frequencies in sublibraries and as background. Mutant frequencies in their respective sublibraries from **Figure 3.21** (page 80) versus mutant frequencies as background from Figure 3.22 (page 80) are plotted as scatter plots for **A)** SL1, **B)** SL2, **C)** SL3, **D)** SL4. Each point represents a single mutant. The point representing WT is labeled on each plot. The dotted lines represents $y = x$ for each plot.

Figure 3.24: Comparison of background mutant frequencies in two independent sequencing experiments. Mutant background frequencies from **Figure 3.22** (page 80) are plotted as a scatter plot against mutant background frequencies from and independent deep sequencing experiment. Each point represents a single mutant. The point representing WT is labeled on each plot. The dotted lines represents $y = x$ for each plot.

Figure 3.25: Final mutant frequencies in DHFR point mutant sublibraries. Mutant frequencies from deep sequencing counts for 4 sublibraries covering all single point mutants are displayed as heatmaps with a cut off of **A)** 1×10^{-4} or **B)** $1 \times 10^{-4.5}$. Rows are labeled by the position in DHFR. Columns are labeled by the amino acid identity. The matrix is split into 4 groups by sublibrary. The matrix is colored by allele frequency according to the heatmap (right).

Figure 3.26: Final background frequencies in DHFR point mutant sublibraries. Background frequencies from deep sequencing counts for 4 sublibraries covering all single point mutants are displayed as heatmaps with a cut off of **A)** 1×10^{-4} or **B)** $1 \times 10^{-4.5}$. Background is assigned based on location the same amplicon reading frame. SL1 is background for SL2, SL2 for SL1, SL3 for SL4, and SL4 for SL3. Rows are labeled by the position in DHFR. Columns are labeled by the amino acid identity. The matrix is split into 4 groups by sublibrary. The matrix is colored by allele frequency according to the heatmap (right).

Frequency $\geq 1 \times 10^{-4.0}$			$>1\times10^{-4.5}$	
Sublibrary	Coverage $(\%)$ Error $(\%)$		Coverage $(\%)$ Error $(\%)$	
	95.7	6.1	98.6	9.7
	95.5	6.4	99.4	9.2
	93.4	5.1	98.5	10.1
	97.2	7.8	99.8	121

Table 3.5: Single point mutant library coverage and background.

3.3.5 Construction of an In-house Turbidostat

We next aimed to build our own turbidstat based off designs and a microcontroller gifted from Victor Salinas in Rama Ranganathan's lab (University of Chicago, formerly UTSW). This turbidostat design uses sterile air flow both to oxygenate and mix the culture and to remove waste medium as fresh medium is added (**Figure 3.2**, page 59). Medium is provided by gravity flow from a 2-5 L source bottle that is clamped by a solenoid valve. The solenoid valve is triggered by a microcontroller that measures the optical density of the growth culture using the voltage across an IR emitter/receiver pair housed in a plastic ring. The turbidostat is housed in an incubator for temperature control.

We encountered two issues when building this turbidostat. First, we observed that the signal from the IR emitter/receiver pair is highly sensitive to the position of the growth chamber. To address this sensitivity, we developed a system to minimize direct contact with the turbidostat while in operation. A laser-cut acrylic sheet secures the sensor ring in position in the incubator, and a sampling loop is used to collect samples without opening the incubator during operation. Second, the positive pressure from the air-pump was greater than the hydrostatic pressure from the medium source. To address the loss of flow, we installed a peristatic pump to provide a constant flow of fresh medium when the microcontroller triggered the pump. This also allowed us to optimize the duration of pump activation to produce dilutions from which growth rates

Figure 3.27: Example OD measurements from the in-house turbidostat during a selection experiment on a library of DHFR single point mutants. The OD600 value inferred from the voltage across an IR emitter-receiver pair is plotted as a function of time. The "clamp" OD value (0.075) is shown as a dashed red line. Decreases in OD correspond to dilution from automatic addition of M9 medium.

could be reliably fit (Figure 3.27, page 86). The final turbidostat was mechanically different from the original design, but adequately functional (**Figure 3.28**, page 87). Taken together with the optimization of selection and construction of the library, we concluded that we were ready to perform DMS on DHFR.

3.3.6 DMS on DHFR Under Optimized Conditions

We next performed deep mutational scanning using the calibrated selection conditions to determine growth effects in biological triplicate for a library of all possible DHFR single point mutants.

3.3.6.1 Selection on all DHFR Single Point Mutants To maintain the culture in early Log phase growth, we performed selections with a turbidostat at a clamp OD of 0.075. To quantify the effects of DHFR mutations on growth, we calculated selection coefficients $[35]$ from the change in allele frequency over time by deep sequencing of timepoint samples. Under these controlled selection conditions (see **Methods, Chapter 3.5.0.6**, page 111) the selection coefficients for these point mutants correlate linearly with growth rates measured in a plate reader as is expected

Figure 3.28: Schematic for the in-house turbidostat. The turbidostat is comprised of a 250 mL pyrex bottle as a growth chamber that is housed in an incubator. The voltage IR emittler/recevier pair measures is passed through an analogue-digital converter (ADC) to calculate a number value for the optical density of the culture. This value is then used to calculate the OD600 equivalent based on a pre-experiment calibration with samples of known OD600. When the OD600 value crosses a user-set threshhold, the controlling software triggers a peristaltic pump to add fresh M9 medium. The culture is mixed and oxygenated by input sterile air, which also provides positive pressure for the removal of excess medium.

because the selection coefficient mathematically relates to the cell doubling rate by a scalar factor (**Figure 3.29A**, page 88, **Table 3.4**, page 72). Furthermore, we observed a linear relationship between selection coefficient and *in vitro* activity at cytosolic substrate concentrations 36 for a panel of 14 DHFR mutants (**Figure 3.30A**, page 89, **Table 3.1**, page 65). These results confirm that selection coefficients between -1.5 and 1.0 in our experiment are correlated with DHFR activity over approximately 3 orders of magnitude, and that selection can resolve mutants with higher turnover than wild-type level activity.

3.3.6.2 Analyzing Noise in Selection Coecients We next analyzed the deep mutational scanning data for all possible DHFR single point mutants under the calibrated selection conditions. All pairwise replicates were related with a Pearson correlation R^2 value of 0.70 and the median standard deviation between replicates for selection coefficients was 0.2 (Figure

Figure 3.29: Error and reproducibility in DHFR DMS. A)Comparison of selection coefficients from Figure 3.30C (page 89) with growth rates measured in a plate reader for monocultures of the selection strain transformed with the SMT205 selection plasmid (**Table 5.2**, page 174) encoding a single DHFR variant (identified by number, in-Figure caption). Error bars reflect the standard deviation over at least three biological replicates. **B)** Comparison of all pairwise replicates for selection coefficients from triplicate deep mutational scanning on DHFR. The Pearson correlation R² value from linear regression was 0.70. **C)** Distribution of standard errors for individual selection coefficients from a single replicate. Selection coefficients are the slope from a linear regression of allele frequency as a function of time in selection. The standard error here is the mean square of residuals. **D)** Distribution of standard deviations of selection coefficients for individual point mutants over replicate experiments. Each mutant had a measured selection coefficient in at least 2 of the 3 replicates. The median of this distribution of standard deviations over all alleles was 0.2 and was used to determine the cut-offs for advantageous and disadvantageous mutations in **Figure 3.30B** (page 89).

Figure 3.30: *E. coli* DHFR deep mutational scanning uncovers many advantageous mutations. **A)** Selection coefficients from deep mutational scanning as a function of enzymatic velocity for purified DHFR point mutants measured *in vitro*. Velocities at 20 *µ*M DHF were calculated from Michalis-Menten parameters. Error bars reflect the standard deviation from 3 biological replicates. **B**) Histogram of selection coefficients. The wild-type value is indicated with a vertical black line. The median standard deviation over all mutations is the cut-off for WTlike behavior (see **Methods**, **Chapter 3.5.0.10**, page 115, **Figure 3.29**, page 88, **Figure 3.31**, page 90) and is indicated with dashed lines. Mutation are colored as advantageous (red), disadvantageous (blue), WT-like (white), or null (grey). **C)** Structural model of DHFR (PDB ID: 3QL3) with cross-section slices (a-e) indicated. The DHF substrate (green) and the NADPH cofactor (purple) are represented by spheres (yellow carbons and heteroatom coloring). An arrow indicates the perspective for each slice. **a-e)** 5 cross-section slices. Color scale indicates numbers of advantageous mutations at each position. Crosshatching indicates residues with >20% solvent accessible surface area.

Figure 3.31: Variation in selection coefficients for DHFR DMS. **A)** Standard deviation of selection coefficients over biological replicates. The data were plotted as a function of a sliding window over all single point mutants sorted by selection coefficient. Each point represents the mean error (biological replicate standard deviation) over 50 consecutive selection coefficients (after sorting by value) and the error bars represent ± 1 standard deviation of the error. The dashed line represents median error over the entire dataset, which was used determine the for WT-like behavior in **Figure 3.30B** (page 89). The dotted line represents $y = x$ for comparison between the magnitude of the error relative to the magnitude of the selection coefficient. **B**) Standard deviation over synonymous codons coding for the same sequence, plotted as in A).

3.31BC, page 90). The standard deviation of selection coefficients for WT synonymous codons was 0.12. From these data, we define DHFR mutations with selection coefficients of < -0.2 and > 0.2 as disadvantageous and advantageous, respectively (**Figure 3.30B**, page 89. This cuto corresponds to the error in the regime of WT-like alleles with selection coefficients $>$ -0.2 and < 0.2 (**Figure 3.31**, page 90).

3.3.7 Functionally Characterized Positions in DHFR are Enriched for Disadvantageous and Null Mutations

Mutations that were depleted during overnight growth in supplemented M9 (see **Methods**,

Chapter 3.5.0.6, page 111) were assigned a null phenotype. As expected, mutations at DHFR positions that are known to be functionally important (M20, W22, D27, L28, F31, T35, M42, L54, R57, T113, G121, D122, and S148) were generally disadvantageous or null mutations (**Figure 3.32**, page 91). These results indicate that our selection assay is a sensitive reporter of

Figure 3.32: Residues previously shown to have a functional role displayed on the DHFR structure. **A-C)** Functionally important residues are colored green, labeled, and shown with slices of the –Lon heatmap (heatmap coloring by selection coefficient is as in Figure 2). The wild-type residue is outlined in black. Positions 22, 27, 35, 57, and 113 are Intolerant, and positions 20, 28, 31, 42, 54, 121, 122, and 148 are Deleterious. In A) the closed (upper, white, PDB ID: 3QL3) and occluded (lower, grey, PDB ID: 1RX4) conformation are shown to illustrate alternate stabilization of the two conformations by D122 (closed)[37] and S148 (occluded)[38]. For all other panels, only the closed conformation is shown.

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Figure 3.33: Growth curves for top advantageous mutations. The absorbance (ABS) at 600 nm was monitored in 96-well plate format for monocultures of the selection strain transformed with strong advantageous mutants (L24V in dark red, W47L in bright red, wild-type in black). The doubling rates (top left in plot) were calculated from the early exponential phase of growth (see **Methods**, **Chapter 3.5.0.4**, page 110). All growth curves are shown as sets of three biological replicates.

functionally important residues and that our results are consistent with previous biochemical characterization of DHFR.

3.3.8 Advantageous Mutations to DHFR

In contrast, the observation of a large fraction of advantageous mutations was unexpected: 737 of 3161 possible variants were advantageous mutations (23.3%), and wild-type DHFR only ranked 1205th. In direct measurements of individual growth rates under our selection conditions, the top two DHFR variants (W47L and L24V) led to increases in growth rate of 40 and 76%, respectively, when compared to wild-type DHFR (**Figure 3.33**, page 92). Advantageous mutations were widely distributed over 127 of the 159 positions of DHFR (**Figure 3.30C**, page 89). Furthermore, when we examined the DHFR structure, many of the advantageous mutations appeared to disrupt key side-chain interactions, for example by disrupting atomic packing interactions or surface saltbridges (**Figure 3.34**, page 93).

Figure 3.34: Example positions with multiple advantageous mutations hypothesized to be destabilizing. **A-C)** Wild-type residues are colored in green on the DHFR structure (PDB ID: 3QL3) and depicted with slices of the –Lon heatmap (heatmap coloring is as in Figure 2). The wild-type residue is outlined in black on the heatmap. Positions 47, 114, and 154 are in the Beneficial category, and position 41 is in the Deleterious category. In the examples here, advantageous mutations appear to disrupt core packing and a surface salt bridge.

3.3.9 Characterizing Top Advantageous Mutations to DHFR

We next sought to test whether advantageous mutations make DHFR a faster enzyme. To select specific mutations for *in vitro* tests, we considered all positions with more than one mutation in the top 100 most advantageous mutations. We describe these positions by their location (**Figure 3.35**, page 94) in one of four structural regions that appear to be hot-spots for the top advantageous mutations: 1) exchanges between hydrophobic residues at core positions, 2) disruptions of surface residues on the beta-sheet near the active site, 3) disruptions of polar interactions with the adenine ring of NADPH, or 4) mutations to the active site or M20 loop that controls access to the active site. At these positions, we selected 24 strongly advantageous mutations for *in vitro* characterization. (**Figure 3.36**, page 95)

3.3.9.1 Measuring DHFR Point Mutant Activities in Lysates The DHFR activity in ER2566 Δ *folA*/ Δ *thyA* lysates was uniformly higher for these advantageous mutants relative to the

Figure 3.35: DHFR structure with mutational hot-spots. **A)** Positions with 2 or more top 100 advantageous mutations displayed on the DHFR structure. The beta carbon is depicted as a sphere scaled according to the number of top mutations. For mutants selected for *in vitro* characterization, the beta carbon is colored according to its location in the DHFR structure: core (purple), surface beta-sheet (gold), proximal to the adenine ring on NADPH (blue), or proximal to the active site and M20 loop (red). Positions for advantageous mutants from the calibration set are depicted in dark grey. **B)** The structure from A) rotated 90° clockwise.

activity for WT DHFR (**Figure 3.37**, page 96). This lysate activity assay reports on both kinetic and expression effects as the product of $[DHFR] \bullet k_{cat}$. These results are consistent with the results from *in vivo* selection.

3.3.9.2 *In vitro* **Velocities for Purified DHFR Point Mutants** We then examined the *in vitro* velocities of these mutants (**Figure 3.38**, page 97). We observed that approximately 2*/*3 of the mutants have velocities equal an up to three-fold higher than that of WT at cytosolic concentrations of DHF. In contrast, approximately 1*/*3 of the mutants have velocities as much as two-fold lower than that of WT in the same DHF concentration regime.

3.3.9.3 Compound Contributions from Multiple Molecular Properties Lead to Increased Growth with Advantageous Mutations We therefore examined the soluble expression level of these mutants

Figure 3.36: Structural context for hotspot residues from **Figure 3.35** (page 94). **A-D)** For each panel, the hot spot region is indicated on a cartoon of DHFR: globular core in purple (A), the beta-sheet surface below the active site in gold (B), the base of the M20 loop in red (C) and the adenosine binding site in blue (D). Slices of the –Lon and +Lon heatmaps are shown for each position within the hot spot region (heatmap coloring is as in Figure 2). The wild-type residue is outlined in black. Positions 30, 47, 85, 102, 114, 116, 154 are in the Beneficial category. Position 24, 25, 62, 91, 92, 156 are in the Mixed category. Positions 41, 42, and 98 are in the Deleterious category. For A-C) the structure shown is PDBID: 3QL3, and for D) the structure shown is PDB ID: 1RX1. In IRX1 (as in 1RX4), R98 is in proximity to the adenine ring. In 3QL3, R98 extends into bulk solvent. Residues within the hot spot cluster are labeled with their residue number.

Figure 3.37: Lysate activity for DHFR wild-type and point mutants on the selection plasmid. **A)** Lysate activity for DHFR variants under selection growth conditions (see **Methods**, **Chapter 3.5.0.14**, page 122) plotted as the rate of change in DHF concentration as a function of time monitored over the window of DHF concentration from 30 μ M to 20 μ M in ER2566 Δ *folA*/ Δ *thyA* lysates. Error bars represent \pm 1 standard deviation from three biological replicates. **B)** Relative lysate activities for DHFR variants. Lysate activities from A) normalized by WT-level of activity.

and observed that mutant expression levels relative to WT levels varied widely from an 8-fold decrease to a 20-fold (**Figure 3.39**, page 100). Combining the data on abundance and velocity, the expected total DHFR activity ([DHFR]*•velocity*) is not a strong quantitative predictor of the advantageous mutants in selection (**Figure 3.40**, page 101, **Figure 3.41**, page 102). We attribute discrepancies at least in part to the difficulty of accurately quantifying rather small differences in activity and abundance, in addition to other potential complicating factors such as differential activity of cellular chaperones for different DHFR variants[39], and feedback regulation that could affect cellular concentrations of the substrate DHF[32, 40]. Nevertheless, our *in vitro* measurement are in qualitative agreement with the *in vivo* selection. Specifically, the majority of advantageous mutants show increased activity compared to WT when considering both velocity and abundance (positions above the line indicating WT activity in **Figure 3.42**, page 103). Taken together, these results suggest that increased selection coefficients arise from an interplay of effects of the mutations on cellular abundance and catalytic activity, and that each parameter

Figure 3.38: *In vitro* velocities of purified DHFR wild-type and point mutants. Velocities were measured at **A)** 5, **B)** 10, **C)** 20, and **D)** 30 *µ*M DHF (**Table 3.6**, page 98). For each mutant, the bar is colored by the mutation's location within the hot spots from **Figure 3.35** (page 94) and **Figure 3.36** (page 95). Error bars represent *±* 1 standard deviation from three independent experiments.

Table 3.6: *In vitro* velocity for selected advantageous mutations measured as described in **Methods** (**Chapter 3.5.0.13**, page 121) at multiple concentrations of DHF are reported with the standard deviation over three independent experiments.

5 μ M DHF		10 μ M DHF		20 μ M DHF		30 μ M DHF		
Variant	Velocity	Std. dv.	Velocity	Std. dv.	Velocity	Std. dv.	Velocity	Std. dv.
WT	2.42	0.75	3.88	0.75	5.12	0.74	5.48	0.37
L24V	2.85	1.05	5.37	1.43	9.01	1.64	10.79	0.86
W30F	2.02	0.37	3.79	0.96	6.77	1.56	8.50	1.94
W30M	2.05	0.98	4.45	1.46	7.73	2.53	10.27	3.03
I41A	1.64	0.52	3.05	0.81	4.69	1.11	4.88	1.06
I41V	2.52	1.71	3.77	2.27	5.11	2.44	5.13	1.96
M42F	3.08	1.40	4.62	1.68	6.42	1.24	6.90	0.64
M42Y	4.45	1.18	7.69	1.41	12.51	1.43	15.16	1.32
H45S	1.26	0.19	2.29	0.21	3.79	0.38	4.73	0.74
W47L	1.06	0.35	1.85	0.44	2.81	0.35	3.62	0.32
W47V	0.74	0.45	1.27	0.68	2.28	0.79	2.90	0.37
L62A	1.03	0.61	1.41	0.71	2.46	1.00	2.30	1.22
L62V	1.74	0.64	2.61	0.64	3.29	0.62	3.60	0.26
C85L	1.56	0.49	2.92	0.63	4.71	0.09	5.77	0.52
191A	3.17	0.64	5.32	0.60	8.08	0.59	8.94	0.49
191G	2.38	0.55	4.33	1.20	7.46	1.46	9.22	1.95
R98Y	1.38	0.68	2.38	0.97	3.83	0.97	4.43	0.53
Q102L	0.84	0.31	1.52	0.43	2.52	0.57	2.77	0.26
Q102W	0.72	0.28	1.27	0.38	1.81	0.61	2.29	0.35
T113V	0.51	0.05	1.19	0.09	2.58	0.04	4.38	0.08
H114V	2.61	1.09	4.12	1.28	5.62	1.08	6.57	1.06
D116I	3.59	1.17	5.37	1.34	7.01	0.95	8.18	0.87
D116M	3.87	1.33	5.66	1.50	7.40	1.21	7.83	0.80
E154V	2.71	0.60	4.66	1.16	7.73	1.82	9.50	2.02
L156Y	3.80	1.66	5.70	1.94	7.43	1.41	7.64	0.82

alone is insufficient to explain the majority of the advantageous mutations.

3.3.9.4 Measuring T*^M* **Values for DHFR Point Mutants** We then measured apparent melting temperature (T*m*) values from non-reversible thermal denaturation monitored by circular dichroism spectroscopy (**Figure 3.43**, page 104), which revealed that many of the advantageous mutations considerably destabilized the protein, and no mutant proteins were more thermostable than WT DHFR.

Table 3.7: Soluble DHFR abundance levels in molecules per cell. Abundances were measured from lysate activity assays as described in **Methods** (**Chapter 3.5.0.14**, page 122). All values are for the SMT205 plasmid transformed into the ER2566 Δ *folA* Δ *thyA*. NM, not measured.

Variant	Molecules per cell	Standard deviation
WT	52.0	9.2
L24V	83.6	6.8
W30F	81.3	2.7
W30M	76.9	0.3
141A	65.6	5.9
141V	177.5	72.8
M42F	1199.1	17.6
M42Y	360.9	2.6
H45S	101.9	10.1
W47L	558.3	94.5
W47V	ΝM	NM
L62A	NM	NM
L62V	112.0	9.4
C85L	67.2	11.6
191A	98.5	3.8
191G	110.7	12.8
R98Y	116.1	16.2
Q102L	239.5	27.0
Q102W	194.9	42.4
T113V	418.3	19.1
H114V	NM	NM
D116I	ΝM	NM
D116M	49.8	4.4
E154V	37.0	5.1
L156Y	47.3	3.1

Figure 3.39: Soluble cellular abundance for DHFR wild-type and point mutants on the selection plasmid. **A)** DHFR cellular abundance calculated from the lysate DHFR activity in **Figure 3.37** (page 96) and *in vitro* kinetics with purified enzyme (see **Methods**, **Chapter 3.5.0.14**, page 122). Error bars represent the cumulative percent error (standard deviation) from three independent experiments for velocity and three biological replicates for lysate activity. **B)** Relative expression of DHFR variants. DHFR abundances from A) normalized by WT-level of abundance. Error bars represent the cumulative percent error as in A).

Figure 3.40: Selection coefficient compared to predictions of WT DHFR and point mutant activity from cellular abundance and *in vitro* velocity measurements. Selection coefficients for selection plotted against DHFR activity calculated as cellular abundance of DHFR times *in vitro* velocities of purified DHFR variants ([DHFR]*•*velocity[DHF]) measured at **A)** 5, **B)** 10, **C)** 20, and **D)** 30 *µ*M DHF (see **Figure 3.38**, page 97, **Table 3.6**, page 98, **Figure 3.39**, page 100, **Table 3.7**, page 99). X-axis error bars represent the cumulative percent error (standard deviation) from three measurements of DHFR concentration and three independent experiments for velocity (see **Methods**, **Chapter 3.5.0.13**, page 121, **Chapter 3.5.0.14**, page 122).Y-axis error bars represent *±*1 standard deviation from biological replicate selection experiments(see **Methods**, **Chapter 3.5.0.10**, page 115).

Figure 3.41: Zoom in for selection coefficient compared to predictions of WT DHFR and point mutant activity from cellular abundance and *in vitro* velocity measurements. Selection coefficients for selection plotted against DHFR activity calculated as cellular abundance of DHFR times *in vitro* velocities of purified DHFR variants ([DHFR]*•*velocity[DHF]) measured at **A)** 5, **B)** 10, **C)** 20, and **D)** 30 *µ*M DHF (see **Figure 3.38**, page 97, **Table 3.6**, page 98, **Figure 3.39**, page 100, **Table 3.7**, page 99). X-axis error bars represent the cumulative percent error (standard deviation) from three measurements of DHFR concentration and three independent experiments for velocity (see **Methods**, **Chapter 3.5.0.13**, page 121, **Chapter 3.5.0.14**, page 122).Y-axis error bars represent *±*1 standard deviation from biological replicate selection experiments(see **Methods**, **Chapter 3.5.0.10**, page 115).

Figure 3.42: Cellular abundance versus *in vitro* velocity for DHFR wild-type and point mutants. Cellular abundance of DHFR vs. *in vitro* velocities of purified DHFR measured at \bf{A}) 5, \bf{B}) 10, \bf{C}) 20, and \bf{D}) 30 μ M DHF (see **Figure 3.38**, page 97, **Table 3.6**, page 98, **Figure 3.39**, page 100, **Table 3.7**, page 99). Points are colored by the mutation's location within the hot spots (**Figure 3.35**, page 94, **Figure 3.36**, page 95). Error bars represent*±*1 standard deviation from three independent experiments (see **Methods**, **Chapter 3.5.0.13**, page 121, **Chapter 3.5.0.14**, page 122). The dashed line represents WT equivalent DHFR activity, where $[DHFR]_{WT}$ ● velocity $_{WT}$ $=[\mathsf{DHFR}]_{mut}$ • velocity $_{mut}.$

Figure 3.43: Thermal denaturation curves monitored by CD signal at 225 nm for selected hotspot mutants. The curves are colored by the mutation's location within the hot spots (**Figure 3.35**, page 94, **Figure 3.36**, page 95). The raw data are shown with thin lines and the fitted curves are shown as thick lines. For each plot, the mutant identity and apparent T_m value are listed in the top left corner.

3.4 Discussion

The experiments in this chapter show the optimization of a selection assay for DHFR activity that can resolve 2-3 fold changes in velocity at cytosolic concentrations of DHF. Selection under these conditions revealed many advantageous mutations to DHFR. We observed that these advantageous mutations show a selection advantage in monoculture and higher lysate activity which results from a combination of expression level effects and changes to the kinetic parameters of the enzyme. We also show that a representative sample of the strongest advantageous mutations show a wide-range of destabilizing impacts.

It is common to conceptualize mutational impacts in terms of activity-stability trade-offs, but it is not immediately evident that destabilization is causal to DHFR activation. It is expected that the set of all single point mutations to DHFR gives rise to a broad range of thermodynamic impacts in which destabilizing mutations more likely. Therefore, selection advantage and stability may be independent properties, and the advantageous mutations we characterized may only represent the underlying global distribution of thermodynamic impacts. There may be no correlation between fold stability and selection coefficients if we measure T_m values for all possible single mutations. Alternatively, protein fold thermostability is by definition a very low resolution metric. It is possible that destabilizing mutations in specific regions (e.g. the hot spots for advantageous mutations) preferentially impact the kinetic parameters of the enzyme. Within these hotspots, there may be more correlation between stability and selection advantage. While the advantageous mutations are spread throughout DHFR (**Figure 3.30C**, page 89), we do not know if these mutations act to increase DHFR activity by a consistent method and if they have similar destabilizing effects. It would be useful to have a broad picture of which mutations destabilize DHFR and how that pattern relates to the pattern of observed advantageous mutations. We will describe experiments

performed to address questions around activity stability trade-offs in **Chapter 4**.

3.4.1 Future Directions

To date, however, we have not used our well-calibrated assay to perform selection on extensive libraries of higher order mutations. There are several interesting questions that we can approach with this powerful tool. One questions is, can a predictive model of epistasis be developed? Recent results from the lab of Rama Ranganathan were used to support a model where mutational impacts of single and double point mutants averaged over a large number of combinatorial backgrounds were more predictive than the measurements of those mutational impacts in the wild-type background alone [41]. What was not clear from this study was whether that increase in predictive power resulted from a fundamental principle of epistasis, or if averaging corrected for noise in the original measurements. Using combinatorial libraries in *E. coli* DHFR and in the background of DHFR orthologues could be a compelling experiment for examining how to predict mutational impacts with both many and few changes to the background sequence.

Taking the line of inquiry on mutational impact, the extent of functional sequence space, and the possibility of predictive models further, we can ask where the pareto front for DHFR actvity lies in sequence space. How far can a sequence differ from DHFR orthologue sequences and still have wild-type level DHFR activity? In **Chapter 2** (page 11), we described and tested a computational method for designing sequences that conformed to multiple structural and energetic constraints. Computational methods may allow us to predict and test sequences on the pareto front for DHFR activity in sequence space. Screening libraries of designed DHFR sequences could also be very powerful for understanding where computational design models work and fail in producing functional DHFR sequences.

Finally, we can expand the number of dimensions when we consider the constraints on

functional sequence space by including perturbations to the environment around DHFR. DHFR sequences that are functional and able to support *E. coli* growth under our current selection conditions may be non-functional in perturbed conditions such as low-folate stress from the antibiotic sulfathiazole or inhibition of TYMS from 5-fluorouracil. Carbon source limitations and anaerobic conditions may greatly change the redox potential within the cell. Temperature will affect expression levels, $\Delta\Delta G_{folding}$, and kinetic rates in many cellular processes. All of these resulting stresses may reshape the DHFR mutational landscape. These types of experiments, and how different mutational landscapes are integrated over time should yield new insights into how organisms adapt and protein sequences evolve.

3.5 Methods

All plasmid and primer sequences are listed in **Table 5.2** (page 174). Key plasmids were deposited in the Addgene plasmid repository and are available at https://www.addgene.org/Tanja_Kortemme. All code and python scripts are available at https://github.com/keleayon/2019_DHFR_Lon.git with key input files and example command lines.

3.5.0.1 Generation of Plasmids for *In Vivo* **Selection** The vector bearing DHFR and TYMS for *in vivo* selection (SMT205) was derived from the pACYC-Duet vector described by Reynolds et al [20]. The lac operon upstream of the TYMS gene was replaced with a Tet-inducible promoter. A Tet promoter fragment had been generated with overlap extension polymerase chain reaction (PCR) and cloned into the pACYC vector (SMT101) at unique AflII/BglII sites to produce SMT201. Selection conditions that resolved increased-fitness mutations were obtained with the SMT205 plasmid where the DHFR "AAGGAG" RBS was replaced with "AATGAG" based on

prediction from the RBS calculator(Salis et al., 2009) using inverse PCR . Briefly, PCR reactions were set up using $2x$ Q5 mastermix (NEB, cat# M0492), 10 ng of plasmid template, and 500 nM forward and reverse primers. PCR was performed in the following steps: 1) 98° C for 30 seconds, 2) 98°C for 10 seconds, 3) 57-63°C for 30 seconds, 4) 72°C for 2 minutes, 5) return to step 2 for 22 cycles, 6) 72 \degree C for 5 minutes. As needed, the annealing temperature (step 3) was optimized in the range of 57-63°C. 25 μ L of RBS reaction was mixed with 1 μ L of DpnI (NEB, cat# R0176), 1 μ L of T4 PNK (NEB, cat# M0201), 1 μ L of T4 ligase (NEB, cat# M0202), and 3.1 μ L of T4 ligase buffer (NEB, cat# B0202) at 37°C for 2-4 hours. The reactions were then transformed into chemically competent Top10 cells and plated on LB agar plates with 35 *µ*g/mL chloramphenicol (Fisher BioReagents, BP904, CAS: 56-76-7, 35 mg/mL in ethanol). The plates were incubated overnight at 37 $^{\circ}$ C. Single colonies were picked and used to inoculate 5 mL of LB medium (10 g Bacto-tryptone (Fisher BioReagent, cat $#$ BP1415, CAS: 73049-73-7), 5 g Bacto-yeast extract (BD Difco, cat# 212720, CAS: 8013-01-2), 10 g NaCl (Fisher BioReagents, cat# BP358, CAS 7647-14-5), 0.186 g KCl (Sigma, cat# P9541, CAS: 7447-40-7), volume brought to 1 L with MilliQ water, autoclaved) $+35$ mg/mL chloramphenicol. Cultures were incubated overnight in 14 mL plastic culture tubes (Falcon, cat $\#$ 352059) at 37°C under 225 rpm shaking. Pellets were collected by centrifugation at 3500 rpm for 10 minutes at 4° C in a swinging-bucket centrifuge (Beckman Coulter, Allegra X-12R) and miniprepped (Qiagen, cat $#$ 27104). Constructs were confirmed by Sanger sequencing (Quintara Biosciences) by alignment to the template sequence in ClustalOmega.

3.5.0.2 Generation of Plasmid Libraries Four sublibraries were generated to cover the entire mutational space of *E. coli* DHFR: positions 1-40 (sublibrary1, SL1), positions 41-80 (sublibrary2, SL2), positions 81-120 (sublibrary3, SL3), and positions 121-159 (sublibrary4,

SL4). The single point mutant library was performed by multiple parallel inverse RBS reactions to substitute an NNS degenerate codon at every codon in DHFR. RBS primers (**Table 5.3**, page 174) were phosphorylated in a 20 μ L reaction with 1 μ L T4 polynucleotide kinase and 1x T4 ligase buffer. Inverse PCR reactions were performed as described above, followed by RBS clean-up (Qiagen, cat# 28104). The cleaned RBS reactions were incubated for 4 hours with 1μ L Dpnl, 1 μ L of T4 ligase, and 3 μ L of T4 ligase buffer. RBS reactions were analyzed by gel electrophoresis using a 1% agarose gel in TAE buffer (20 mM acetic acid (Sigma Aldrich, cat#, 695092), 2 mM ethylenediaminetetraacetic acid (EDTA) (ACROS Organics, cat $\#$ AC118432500, CAS: 60-00-4), 40 mM Tris, pH 8.5) with 0.01% v/v GelRed (Biotium, cat# 41003), and the product amount was quantified using gel densitometry in the FIJI image processing software package[42]. Samples were pooled stoichiometrically, cleaned once with a gel extraction kit (Qiagen, cat# 28115), and again with a RBS clean-up kit. The pooled and cleaned ligation products were transformed into *E. coli* Top10 cells by electroporation (BioRad GenePulser Xcell, 1 mm path length cuvette (cat# 165-2089), 1.8 kV, time constant \sim 5 ms) using \sim 5 μ L to obtain a minimum of 107 transformants as measured by dilution plating on LB-agar plates with 35 *µ*g/mL chloramphenicol. The transformed cells were rescued in SOB medium (20 g Bacto-tryptone, 5 g Bacto-yeast extract, 0.584 g NaCl, 0.186 g KCl, 800 mL MilliQ water, pH 7.0, volume brought to 1 L with MilliQ water, autoclaved) without antibiotics for 45 minutes at 37°C before culturing overnight in 10 mL SOB medium with 35 μ g/mL chloramphenicol. In the morning, glycerol stocks were made by mixing 500 *µ*L of saturated culture with 500 μ L of sterile filtered 50% (v/v) glycerol. 5 mL of the culture was used to miniprep the transformed library with a Qiagen miniprep kit.

Generation of Individual Point Mutant Plasmids Point mutants in all DHFR-containing plasmids were generated via inverse PCR as described above for the generation of SMT205 except that the appropriate antibiotic was matched with the plasmid (**Table 5.2**, page 174). Library primer sequences (**Table 5.3**, page 174) were used except that the "NNS" sequence on the forward primer was replaced with the desired codon.

3.5.0.3 Generation of ER2566 Δf olA/ Δt hyA –Lon The ER2566 Δf olA/ Δt hyA –Lon strain was generated as previously described[20] and a gift from Prof. Stephen Benkovic.

3.5.0.4 Plate Reader Assay for *E. coli* **Growth** Growth rates for the selection strains bearing individual DHFR mutants were measured in 96-well plate growth assays as described for one individual mutant. The SMT205 plasmid was transformed via heat shock into chemically competent ER2566 Δ *folA*/ Δ *thyA* \pm Lon cells and plated on an LB-agar plate with 30 μ g/mL chloramphenicol plus 50 μ g/mL thymidine and incubated overnight at 37 $^{\circ}$ C. On the second day, 2 mL M9 medium (1x M9 salts (BD Difco, cat# 248510), 0.4% glucose w/v (Fisher Chemical, cat# D16, CAS: 50-99-7), 2 mM MgSO4 (Sigma Aldrich, cat# 63138, CAS:10034-99-8)) with supplements for deficient folate metabolism (50 μ g/mL thymidine (Sigma Aldrich, cat# T1895, CAS: 50-89-5), 22 *µ*g/mL adenosine (Sigma Aldrich, cat# A9251, CAS: 56-61-7), 1 *µ*g/mL calcium pantothenate (TCI, cat# P0012, CAS: 137-08-6), 38 *µ*g/mL glycine (Fisher BioReagents, cat# BP381, CAS: 56-40-6), and 37.25 μ g/mL methionine (Fisher BioReagents, cat# BP388, CAS 63-68-3)) and 30 *µ*g/mL chloramphenicol in a 14 ml culture tube was inoculated with 5-10 colonies scraped from the plate and incubated at 37° C at 225 rpm shaking for 12-14 hours. Biological replicates were obtained from separate inoculations at this step and run on the same plate. All assays were run from fresh transformations. Then, 20 - 50 *µ*L of the

previous culture was used to inoculate 5 mL of M9 medium (no supplements) with 30 *µ*g/mL chloramphenicol in a 14 ml culture tube. This fresh culture was incubated for 6 hours at 30° C at 225 rpm shaking. Meanwhile 2 mL of M9 medium with 30 *µ*g/mL chloramphenicol and a transparent 96-well plate were pre-warmed at 30° C. After the 6-hour incubation, the optical density at 600 nm (OD600) of the culture was measured on a Cary 50 spectrophotometer over a path of 1 cm. This early log-phase culture was diluted to an $OD600 = 0.005$ in the 2 mL aliquot of warmed M9. 200 *µ*L of the dilute culture was pipetted into a well in the 96-well plate. Technical replicates were obtained by dispensing the same dilute culture into multiple wells. Wells were covered with 50 μ L of mineral oil (Sigma Aldrich, cat $\#$ M5904, CAS: 8042-47-5) using the reverse pipetting technique. The plate was then incubated for 20-48 hours at 30° C in a Victor X3 multimode plate reader (Perkin Elmer). Every 10 minutes, the plate was shaken for 30 seconds with an orbital diameter of 1.8 mm under the "normal" speed setting. Then, the absorbance at 600 nm (ABS600) was measured for each well. Growth rates were calculated from the slope of $\text{Log}_2(\text{ABS600} - \text{ABS600}_{t=0})$ for \triangle ABS600 in the range of 0.015 – 0.04 using an in-house python script.

3.5.0.5 Construction of a Turbidostat

3.5.0.6 Deep Mutational Scanning Selection Assay Competitive growth under selection for DHFR activity was performed in a continuous culture turbidostat (gift of Rama Ranganathan) as described below for a single sublibrary. Sublibraries of DHFR single point mutants were transformed via electroporation as described above into electrocompetent ER2566 Δ *folA*/ Δ *thyA* \pm Lon cells using approximately 50 ng of plasmid DNA and 80 μ L of competent cells with a transformation efficiency of 1×10^8 cfu/ng (based on testing with 10 ng of pACYC

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plasmid DNA). Immediately after electroporation, the cells were rescued with 2 mL of SOB medium with 50 μ g/mL thymidine warmed to 37°C. The rescue culture was incubated at 37°C for 45 minutes at 225 rpm shaking. After the rescue step, 4 *µ*L of the rescue medium (1/500 of the rescue volume) was serially diluted in 10-fold increments. Half the volume of each dilution $(1/1000 - 1/10⁷$ of the rescue volume) was plated on an LB-agar plate with 30 μ g/mL chloramphenicol plus 50 μ g/mL thymidine and incubated overnight at 37 $^{\circ}$ C. The colonies were counted the following morning to check for a minimum of 1,000x oversampling of the theoretical diversity in the library $(-10^6$ transformants for each sublibrary). Meanwhile, the larger portion of the rescue medium was mixed with 4 mL of SOB medium with 45 *µ*g/mL chloramphenicol (1.5x) plus 50 μ g/mL thymidine warmed to 37°C. This 6 mL culture was incubated for 5-6 hours at 37° C at 225 rpm shaking in a 14 mL culture tube. After incubation, the culture was pelleted by centrifuging for 5 minutes at 3000 rpm at room temperature in a swinging bucket centrifuge. The cells were resuspended in 50 mL of supplemented M9 medium $+$ 30 μ g/mL chloramphenicol and incubated for 12-14 hours at 37°C at 225 rpm shaking in a 250 mL flask. In the morning, 150 mL of supplemented M9 medium + 30 *µ*g/mL chloramphenicol in a 1 L flask was inoculated with 15 mL of the overnight culture. This pre-culture was incubated at 30° C for 4 hours at 225 rpm shaking. After 4 hours, the pre-culture was centrifuged at 3000 rpm for 5 min at room temperature in a swinging bucket centrifuge, and the OD600 was measured to ensure that the culture did not grow beyond early-mid log phase $(OD600 \sim 0.3)$. The supernatant was decanted, and the pellet was resuspended in 30 mL of M9 medium. Pelleting and resuspension were repeated for a total of 3 washes to remove the supplemented medium. After 3 washes, the OD600 was measured for the resuspended pellet using a 10-fold dilution to stay in the linear range of the spectrophotometer.

The washed pellet was then transferred to the growth chamber of the turbidostat (a 250 mL pyrex bottle) containing 150 mL of M9 medium with 50 *µ*g/mL chloramphenicol. Selection experiments were performed with 2 of the 4 sublibraries at a time (two repeats of SL1-SL2 and SL3-SL4, and one repeat of SL1+SL3 and SL2+SL4 for a net of biological triplicates for every codon in the gene), and the resuspended pellet from each library was diluted in the initial culture to an $OD600 = 0.035$. Mixing and oxygenation was provided by sterile filtered air from an aquarium pump. Every 60 seconds, the aquarium pump was stopped, and the optical density of the culture was read by an infrared emitter-receiver pair. The ADC (analog-to-digital converter) of the voltage over the receiver was calibrated against a spectrophotometer to convert the signal into an approximate OD600. The cells were grown at 30° C with an OD600 threshold of 0.075. When the OD600 of the selection culture exceeded the threshold, the selection culture was diluted to OD600 ~0.065 with 25 mL of M9 medium with 50 *µ*g/mL chloramphenicol, and the additional culture volume was driven through a waste line by the positive pressure of the aquarium pump.

At timepoints of t=0, 2, 4, 6, 8, 12, 16, and 18 hours, 6 mL of the selection culture in 2 mL centrifuge tubes was pelleted at 5000 rpm for 5 minutes at 4° C in a microcentrifuge (Eppendorf, 5242R). The supernatant was removed except for the last \sim 200 μ L, and the tubes were again pelleted at 5000 rpm for 5 minutes at 4° C in a microcentrifuge, and all the supernatant was carefully removed from the pellet. The pellets were stored at -20° C until sequencing.

3.5.0.7 Preliminary Deep Mutational Scanning Assay Using the Turbidostat in the Reynolds Lab at UT Southwestern Preliminary selection on a library of NNS degenerate codon substitutions at the first 40 positions of DHFR was performed essentially as described above in section "Deep Mutational Scanning Selection Assay" (**Chapter 3.5.0.6**, page 111) but with a few modifications.

3.5.0.8 Amplicon Generation Amplicons were generated by two rounds of PCR. The first round of PCR amplifies a portion of the DHFR gene from the pACYC plasmid containing 2-3 sublibraries. For quality control templates were 1 ng/*µ*L plasmid solutions and the amplicons covered SL1-SL2 or SL3-SL4. Round 1 PCR reactions were set up using $1 \mu L$ of template, 1% v/v Q5 hotstart polymerase (NEB, cat# M0493), 1x Q5 Reaction Buffer, 1x Q5 High GC Enhancer, 200 μ M dNTPs, and 500 nM forward and reverse primers. PCR was performed in the following steps: 1) 98 $^{\circ}$ C for 30 seconds, 2) 98 $^{\circ}$ C for 10 seconds, 3) 57 $^{\circ}$ C for 30 seconds, 4) 72 $^{\circ}$ C for 12 seconds, 5) return to step 2 for 16 cycles, 6) 72° C for 2 minutes.

The Round 2 PCR uses primers that attach the Illumina adapters and the i5 (reverse) and i7 (forward) barcodes for sample identification and demultiplexing. Round 2 PCR reactions were set up and run identically to Round 1 reactions except that the template was 1 *µ*L of Round 1 PCR. Round 2 reactions were analyzed by gel electrophoresis using a 1% TAE-agarose gel in TAE buffer with 0.01% v/v GelRed, and the product amount was quantified using gel densitometry in FIJI. Samples were pooled stoichiometrically and cleaned with a gel extraction kit (Qiagen). Because of the risk of contamination from small primer dimers, gel extraction was performed with very dilute samples. Only 20 *µ*L of sample was loaded onto a 50 mL TAE-agarose gel (OWL EasyCast, B1A) with 8 of the 10 wells combined into a single well. The pooled amplicons were then cleaned again with a PCR clean-up kit (Zymogen, cat $#$ D4013) to allow for small volume elution. The final amplicon concentration was measured with a NanoDrop One UV spectrophotometer and by Picogreen assay (Thermo Scientific, cat $#$ P11496).

3.5.0.9 Sequencing for Deep Mutational Scanning Experiments Templates for amplicon PCR were prepared from the frozen pellets. The pellets were resuspended in 20 *µ*L of autoclaved MilliQ water and incubated on ice for 10 minutes. The samples were then centrifuged at 15,000 rpm for 10 minutes at 4° C in a benchtop microcentrifuge. 1 μ L of the supernatant was used as template in the amplicon generation protocol for sublibraries described above. The amplicons were sequenced on an Illumina NextSeq using a 300-cycle 500/550 high-output kit. Because of the limitations in the number of sequencing cycles on the Illumina NextSeq, the full amplicon was not sequenced for amplicons containing non-adjacent sublibraries $(SL1+SL3,$ and $SL2+SL4$). Reads were demultiplexed into their respective selection experiment and timepoint using their TruSeq barcodes. Paired end reads were joined using FLASH[43]. For amplicons with adjacent sublibraries (SL1-SL2 and SL3-SL4), the joined reads were kept. For amplicons with distal sublibraries $(SL1+SL3$ and $SL2+SL4$, the unjoined reads were kept. Reads from all lanes of the Illumina chip were concatenated and raw counts of DHFR mutants were obtained from these reads.

Reads on the Illumina NextSeq (two-color chemistry, LED optics) generally have lower quality scores than reads from the Illumina MiSeq (four-color chemistry, laser optics). This lower quality leads to a background signal. This background was estimated from a WT sample. The median $+$ 1 standard deviation value of background count was subtracted from every allele and the alleles were translated into the amino acid sequence, combining synonymous sequences. Counts at each timepoint were only reported for an allele if its frequency was above 2.0×10^{-5} .

3.5.0.10 Analysis of Deep Mutational Scanning Data Mutant counts were used to generate selection coefficients on our background-subtracted count files with Enrich2 using unweighted linear regression[35]. The raw Enrich2 values for each unique selection experiment were combined with a post-processing script. Enrich2 does not calculate selection coefficients for mutants that have no counts at a timepoint, so some selection coefficients were recalculated using only the timepoints before the counts for that allele fell below the cutoff frequency of 2×10^{-5} . Individual selection coefficients were evaluated based on two criteria: noise and number of timepoints. Individual selection coefficients were discarded 1) if the standard error from regression was greater than $0.5 + 0.5 \times$ selection coefficient or 2) if there were fewer than 4 timepoints reporting on the mutant. The regression for the fitness value of the mutants from replicate selection experiments to the average values across all experiments was calculated and the fitness values in each replicate were scaled to correct for linear differences in the selection values between replicates. These normalized values were then averaged for the final fitness value. Averaged selection coefficients values were evaluated based on two criteria: the standard deviation of the averaged selection coefficients and the number of replicates. Averaged selection coefficients were discarded 1) if the standard deviation over the normalized replicates was greater than $0.5 + 0.25 \times$ |selection coefficient| or 2) if there were fewer than 2 replicates. In **Table 5.5** (page 179) the fitness is reported as the mean normalized fitness, the standard error is reported as the combined Enrich2 standard error (from linear regression of timepoints), and the standard deviation is reported as the standard deviation of the biological replicates.

Selection was evaluated by comparing selection coefficients to DHFR velocity from reported Michaelis-Menten kinetics at cytosolic concentrations of DHF[36]. Kinetic values are listed in **Table 3.1** (page 65)

Based on this calibration, differences between selection coefficients below \sim -2.5 were not considered interpretable, and a floor value of -2.5 was applied to all selection coefficients for the purpose of analysis.

For subtraction to calculate Δ selection coefficients, null selection coefficients in +Lon selection were substituted with the lowest measured selection coefficient. Mutations with a null selection coefficient in –Lon selection were assigned a Δ selection coefficient of "No data" (colored black).

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Mutations with "No data" value in either selection condition were also assigned a Δ selection coefficient of "No data" here.

For clustering of positions, an in-house Python script was used for K-means clustering of positions into categories based on general mutational response at a position (i.e discarding the amino acid identities of the mutants). Spatial clustering was performed based on selection coefficient with distance between two positions calculated in the following steps: 1) sorting the vectors of selection coefficients for each position, 2) trimming the vectors to match vector lengths after discarding "no data" values, 3) calculating a Δ vector by subtracting the two sorted and trimmed vectors, and finally calculating the distance as the mean of the absolute value of the Δ vector. For the first round, categories were seeded with virtual positions that have prototypical mutational profiles for the 5 categories (Beneficial, Tolerant, Mixed, Restricted, and Intolerant). From this first round, all positions in DHFR were categorized into initial clusters. In subsequent rounds, the virtual positions were removed and candidate positions were compared to the non-self positions populating each cluster. The distance between a candidate position and a cluster of positions is calculated as the average of the distance between the candidate position and the three closest non-self positions in the cluster. Clustering was performed over 10 rounds following the initial seeded round, and convergence was confirmed by observing that 5 repetitions gave identical clusters.

3.5.0.11 Western Blot for Untagged and FLAG-tagged DHFR Constructs LB agar plates with 50 μ g/mL thymidine were streaked from frozen stocks and incubated overnight at 37 $^{\circ}$ C. The next day, 2 mL of LB medium with 50 *µ*g/mL thymidine were inoculated with a single colony picked from each plate and cultured overnight at 37° C. The next day, 20 μ L of overnight culture was used to inoculate two cultures 6 mL of LB medium with 50 *µ*g/mL thymidine. This fresh culture was incubated for ~4 hours at 30°C or 42°C at 225 rpm shaking until the OD600 value was between 0.3 and 0.5 on a Cary 50 spectrophotometer over a path of 1 cm. 2 mL of each culture was pelleted by centrifugation at 5000 rpm for 5 minutes at 4° C in a benchtop microfuge, and the supernatant was carefully removed from the pellet, and the pellet was stored at -80 $^{\circ}$ C until the next step.

The pellets were then resuspended with a $1x$ dilution of $4x$ Laemmli buffer (BioRad, $cat#161-0747$) with 10% beta-mercaptoethanol. Volumes for lysis were calculated according to the formula: lysis volume $=$ (volume of culture for pellet) \times (OD600 of culture for pellet) \times (150 μ L Laemmli buffer). The resuspended samples were then boiled at 95^oC for 10 minutes and then allowed to cool to room temperature. 2 *µ*L of Precision Plus Dual Color Standards (BioRad, cat# 1610374) 5 μ L of each sample was then loaded onto a precast 12-well 4-20% tris-glycine PAGE gel (BioRad, cat $#$ 4561095) and developed at 100 V for 90 minutes. Proteins were then transferred to the blot using a wet transfer protocol. The transfer was run in a buffer of (25 mM Tris base, 200 mM glycine with 20% v/v methanol in water) with a voltage source set to limits of 75 V/150 mA for 150 minutes. Once transfer was complete and confirmed by ladder transfer, the nitrocellulose blot was placed in a clear plastic dish, and 20 mL of TBS-T with 3% dry milk buffer solution was added. The nitrocellulose blot was blocked for 1 hour at room temperature on a rocker. The buffer solution was then decanted and replaced with a fresh 20 mL buffer solution. 2 μ L of $(1:10,000)$ of polyclonal rabbit anti-DHFR antibody (gift of Kimberly Reynolds) or monoclonal rabbit anti-FLAG (DYKDDDDK) antibody (Cell Signalling, cat $\#14793S$) was added to the buffer and incubated overnight at 4 $^{\circ}$ C on a rocker. Then, the nitrocellulose blot was washed three times with 20 mL TBS-T buffer, with 5 minutes of incubation at 4° C on a rocker for the last two washes. The TBS-T was decanted

and replaced with 20 mL of TBS-T with 3% dry milk. 2 μ L of (1:10,000) of monoclonal mouse anti-rabbit antibody-HRP conjugate (Millipore, $cat#$ MAB201P) was added to the buffer and incubated for 1 hour at 4° C on a rocker. The Super SignalTM West Pico stable peroxide and enhancer solution were equilibrated at room temperature while protected from light exposure. Then, the nitrocellulose blot was washed three times with 20 mL TBS-T buffer, with 5 minutes of incubation at 4° C on a rocker for the last two washes. 4 mL of the Pico substrate solution was prepared according to instructions, and the nitrocellulose membrane was incubated with the substrate for 5 minutes at room temperature. The nitrocellulose blot was then wrapped in plastic wrap and the chemiluminescence was imaged on a BioRad ChemImager for 6 seconds at normal sensitivity (2×2 downsampling). A second whitefield image was collected for superposing.

3.5.0.12 Purification of His6**-tagged DHFR** DHFR variants were expressed from pHis8 plasmids $(KR101/SMT301)$ for nickel affinity purification as described for one DHFR variant. The plasmid bearing the his-tagged DHFR mutant was transformed via heat shock into chemically competent ER2566 Δ *folA*/ Δ *thyA* –Lon cells, then the cells were plated on LB-agar plates containing 50 *µ*g/mL kanamycin (AMRESCO, cat# 0408, CAS: 25389-94-0, 50 mg/mL in ethanol) and 50 mg/mL thymidine. The plates were incubated overnight at 37° C. The next day 2 mL of LB medium with 50 *µ*g/mL kanamycin was inoculated with a single colony. This culture was incubated overnight at 37° C at 225 rpm shaking. The next day, 25 mL of TB medium (12 g Bacto-tryptone, 24 g Bacto-yeast extract, 0.4% glycerol v/v (Sigma Aldrich, cat# G7893, CAS: 56-81-5), brought to 900 mL with MilliQ water, autoclaved, cooled, mixed with 100 mL sterile filtered buffered phosphate (0.17 M KH2PO4 (Sigma Aldrich, cat $\#$ P0662, CAS: 7778-77-0), 0.72 M K2HPO4 (Sigma Aldrich, cat# P550, CAS: 16786-57-1))) with 50

 μ g/mL kanamycin in a 50 mL conical tube was inoculated with 100 μ L of the overnight culture. The culture was grown at 37° C until the OD600 reached 0.5-0.6. Then, the culture was induced with 0.25 mM isopropyl *β*-D-1-thiogalactopyranoside (IPTG) (Gold Biotechnology, $cat# 12481C100$, CAS: 367-93-1, 1M in autoclaved water, sterile filtered) and incubated for 18 hours at 18° C at 225 rpm shaking. The cultures were pelleted by centrifugation at 3000 rpm for 5 minutes at 4° C in a swinging-bucket centrifuge, the supernatant was discarded, and the pellet was resuspended by pipetting in 4 mL/g-pellet of B-PER (ThermoScientific, cat# 78266) with 1 mM phenylmethylsulfonyl fluoride (PMSF) (Millipore Sigma, cat# 7110, CAS: 329-98-6, 100 mM in ethanol), 10 *μ*g/mL leupeptin (VWR Chemicals, cat# J583, CAS: 26305-03-3, 5 mg/mL in water), and 2 *µ*g/mL pepstatin (VWR Chemicals, cat# J580, CAS: 103476-89-7, 2 mg/mL in water). The lysates were incubated at room temperature for 30 minutes on a rocker and clarified by centrifugation at 3000 rpm for 5 minutes at 4° C in a swinging-bucket centrifuge. The lysate supernatant was then transferred to a fresh 50 mL conical tube and incubated for 30 minutes with 20 μ L of NiNTA resin pre-equilibrated in Nickel Binding Buffer (50 mM Tris base (Fisher BioReagents, cat $#$ BP152, CAS: 77-86-1) pH 8.0, 500 mM NaCl, 10 mM imidazole (Fisher Chemical, cat $#$ 03196, CAS: 288-32-4), and then supernatant was removed by pipetting. The resin was washed 3 times for 5 minutes with 1 mL of Nickel Binding Buffer. Then the protein was eluted into 200 μ L of Nickel Elution Buffer (100 mM Tris pH 8.0, 1 M NaCl, 400 mM imidazole) and dialyzed against DHFR Storage Buffer (50 mM Tris pH 8.0, 300 mM NaCl, 1% glycerol v/v) in 3000 Da MW cut-off Slidalyzer dialysis cups (Thermo Scientific, cat# 88401) at 4 \degree C. After 4 changes of dialysis buffer over 24 hours, the protein was aliquoted, flash frozen in liquid nitrogen, and stored at -80° C. Proteins were purified to \sim 90-95% purity as judged from PAGE gel analysis.

3.5.0.13 *In Vitro* **Assay for DHFR Velocity and Michaelis-Menten Kinetics** *In vitro* measurements of DHFR velocity were carried out by monitoring the change in UV absorbance. For each mutant screened, a purified enzyme aliquot was thawed and centrifuged at 15,000 rpm for 5 minutes at 4° C in a benchtop microcentrifuge. The soluble enzyme was then transferred to a fresh tube, and the concentration was measured by UV absorption on a Nanodrop. Molar concentration of DHFR was calculated using an extinction coefficient of 33585 M^{-1} cm⁻¹ at 280 nm for all variants with the following exceptions: 28085 (W30F/M, W47L/M), 35075 (M42Y, R98Y, L165Y), or 39085 (Q102W) M^{-1} cm⁻¹. The enzyme was diluted to 555 nM in DHFR storage buffer. A pre-reaction mixture was prepared in MTEN buffer (5 mM 2-ethanesulfonic acid (MES) (Sigma Aldrich, cat $#$ 69889, CAS: 145224-94-8), 25 mM ethanolamine (Sigma Aldrich, cat# E6133, CAS: 2002-24-6), 100 mM NaCl, 25 mM Tris base, pH to 7.0) with 55.5 nM enzyme, 111 *µ*M NADPH (Sigma Aldrich, cat# N7505, CAS: 2646-71-1) and 5 mM dithiothreitol (DTT) (GoldBio, cat# DTT25, CAS: 27565-41-9, 1M in water, sterile filtered). The pre-reaction mixture and a micro quartz cuvette (Fisher Scientific, cat $\#$ 14-958-103, 10 mm path length, 2 mm window width) were preincubated at 30 $^{\circ}$ C. The reaction was started by adding 20 μ l of 500 μ M DHF (Sigma Aldrich, cat# D7006, CAS: 4033-27-6) in MTEN with 5 mM DTT to 180 μ L of pre-reaction mixture. The substrate solution was made fresh from a sealed ampule on the day of the experiment. The reaction was briefly mixed by pipetting and then the reaction was monitored by reading the absorbance at 340 nm with an interval of 0.1 seconds in a Cary 50 spectrophotometer with the Peltier temperature set to 30° C. The reactions were allowed to run to completion to establish the baseline, which was subtracted from the absorbance values. The real-time concentration of DHF was calculated by dividing the normalized absorbance values by the decrease in absorbance at 340 nm for the reaction, $0.0132 \ \mu M^{-1}$ cm⁻¹, the velocity of the reaction was calculated as the slope of linear regression to a 30 second window with a mean DHF concentration equal to 5, 10, 20, or 30 *µ*M. Final velocities were normalized to enzyme concentration.

Michaelis-Menten kinetics were performed as described above using 1-5 *µ*M DHFR for concentrations of DHFR from 0.5-100 *µ*M. Initial velocities were estimated from linear regression to the absorbance divided by the decrease in absorbance at 340 nm for the reaction, and then they were fit to the Michaelis-Menten equation using the non-linear least squares method in R.

3.5.0.14 Determining DHFR Activity and Concentration in Cell Lysates The cellular activity of DHFR was measured in cell lysates, and then used to calculate DHFR cellular abundance using a method adapted from previous studies[29, 30]. For each characterized DHFR variant, a plasmid (WT DHFR in plasmids SMT102, SMT201, SMT202 and SMT205 with modified promoters and RBSs or DHFR single point mutants in the final selection plasmid SMT205, see **Table 5.2**, page 174) was transformed via heat shock into chemically competent ER2566 $\Delta f \frac{\Delta f}{\Delta t}$ *±* Lon cells, which were plated on an LB-agar plate with 30 *µ*g/mL chloramphenicol plus 50 μ g/mL thymidine and incubated overnight at 37 $^{\circ}$ C. On the second day, 2 mL M9 medium with supplements for deficient folate metabolism (50 *µ*g/mL thymidine, 22 *µ*g/mL adenosine, 1 *µ*g/mL calcium pantothenate, 38 *µ*g/mL glycine, and 37.25 *µ*g/mL methionine) and 30 *µ*g/mL chloramphenicol in a 14 ml culture tube was inoculated with a single colony scraped from the plate and incubated at 37° C at 225 rpm shaking for 12-14 hours. Three biological replicates were obtained from separate single colonies at this step, and all biological replicates were processed in parallel for subsequent steps. All assays were run from fresh transformations. 20-50 *µ*L of the previous culture were used to inoculate 20 mL of M9 medium (no supplements) with 30 *µ*g/mL chloramphenicol in a 50 ml conical tube. This fresh culture was incubated for 12-18

hours at 30° C at 225 rpm shaking until the OD600 value was between 0.3 and 0.5 on a Cary 50 spectrophotometer over a path of 1 cm. The cultures were pelleted by centrifugation at 3000 rpm for 5 minutes at $4^{\circ}C$ in a swinging-bucket centrifuge, the supernatant was discarded, and the pellet was thoroughly resuspended in 1.1 mL of M9 medium. 1 mL of the resuspension was transferred to a 1.5 mL Eppendorf tube, and the sample was pelleted at 5000 rpm for 5 minutes at 4° C in a microcentrifuge. The supernatant was carefully removed from the pellet, and the pellet was stored at -80 $^{\circ}$ C until the next step. The remained 100 μ L of resuspended pellet was mixed with 900 *µ*L and the OD600 value was measured for each pellet to determine the number of cells in the pellet, with a conversion factor of 8×10^8 cells/mL at OD600 = 1.0. Pellets for positive (ER2566) and negative (ER2566 Δ *folA*/ Δ *thyA* \pm Lon) control samples were collected in a similar fashion, except that antibiotics were not used and initial plates were streaked from glycerol stocks. Additionally, the M9 medium for ER2566 Δf olA $/\Delta t$ hyA \pm Lon contained folate supplements in every step.

Cell pellets were lysed in B-PER with 1 mM PMSF, 10 *µ*g/mL leupeptin, and 2 *µ*g/mL pepstatin. Volumes for lysis were calculated to have consistent lysate concentration according to the formula: lysis volume = (volume of resuspended pellet) \times (OD600 of resuspended pellet) \times (30 μ L BPER lysis buffer). Pellets were resuspended by pipetting in the calculated volume, and the lysates were incubated at room temperature for 30 minutes on a rocker. The lysates were then clarified by centrifuged at 15,000 rpm for 5 minutes at 4° C in a benchtop microcentrifuge. Lysates were kept on ice while the reactions were prepared.

Measurements of DHFR activity in lysates were carried out by monitoring the change in UV absorbance in a BioTek Synergy H1 multimode plate reader. A 180 *µ*L pre-reaction mixture was prepared with MTEN buffer (5 mM MES, 25 mM ethanolamine, 100 mM NaCl, 25 mM Tris base, pH to 7.0), 111 μ M NADPH, 5 mM DTT, and containing 20 μ L lysate. The pre-reaction mixtures in a UV transparent 96-well plate (Grenier Bio-One, cat $#$ 655809) were pre-incubated at 30 $^{\circ}$ C for 10 minutes. The substrate solution of 500 μ M DHF in MTEN with 5 mM DTT was made freshly from a sealed ampule of DHF on the day of the experiment. The reaction was started by automatic injection of 20 *µ*l of 500 *µ*M DHF in MTEN with 5 mM DTT into each well with pre-reaction mixture. The plate was then orbital shaken for 1 minute at 365 rpm with a 2 mm amplitude. The reaction was briefly mixed by pipetting and then the reaction was monitored by reading the absorbance at 340 nm with an interval 1 minute for 2 hours while incubating at 30° C. To establish a baseline for accurate calculation of DHF concentration in each well, 50 μ L of 1 μ L WT DHFR in DHFR storage buffer was injected into each well, the plate was then orbital shaken for 1 minute at 365 rpm with a 2 mm amplitude, and the reactions were allowed to run to completion over 10 minutes, before a final reading of absorbance at 340 nm was taken. In processing, this baseline value was subtracted from the absorbance values for each well. The real-time concentration of DHF was calculated by dividing the normalized absorbance values by the decrease in absorbance at 340 nm for the reaction, $0.0132 \ \mu M^{-1}$ cm⁻¹, times a correction factor of 1.5 for calibration between the plate reader and the absorbance at 340 nm using a Cary 50 spectrophotometer with a 1 cm pathlength quartz cuvette. The velocity of the reaction was calculated as the slope of linear regression for DHF concentration as a function of time over a window of DHF concentration from 20 to 30 *µ*M. The mean slope of the negative control wells (untransformed ER2566 Δ *folA*/ Δ *thyA* \pm Lon) was subtracted from all wells as a baseline. The linear regression of *in vitro* DHFR reactions using purified enzyme over the same window of DHF concentration from 20 to 30 *µ*M was calculated from measurements described above (**Chapter 3.5.0.13**, page 121, **Table 5.6**, page 243, and the DHFR abundance in each well was calculated
from the ratio of activity*lysate*/velocity*purif iedenzyme*. The number of DHFR molecules per cell was then calculated by dividing the total number of DHFR molecules in each 200 *µ*L of reaction by the number of cells in 20 μ L of lysate based on the OD600 measurements.

3.5.0.15 CD Spectroscopy Samples for circular dichroism (CD) spectroscopy were prepared at a concentration of 10 μ M in a buffer of 150 mM NaCl and 50 mM Tris, pH 8.0. CD spectra acquisition and thermal denaturation was carried out in a Jasco J-715 CD spectrometer using a cuvette with a 2 mm pathlength (Starna Cell Inc., cat $#$ 21-Q-2). For each DHFR variant, a predenaturation spectra was recorded between 207 nm and 280 nm where the high tension voltage was below 600 V. Thermal denaturation data was collected at 225 nm with a bandwidth of 2 nm, a response time of 8s, and a resolution of 0.1 $^{\circ}$ C during heating at a rate of 1 $^{\circ}$ C/min. When the curve flattened, the sample was removed from the CD spectrometer and the system was returned to 30° C. The sample was returned to the chamber and allowed to equilibrate for 10 minutes. A post-denaturation spectrum was recorded after equilibration. Between samples, the cuvette was cleaned with sonication in Hellmanex III (Hellma, cat $#$ 2805939) followed by washing with 50% concentrated nitric acid. Thermal denaturation was found to be only partially reversible based on comparisons of spectra recorded before and after denaturation. Thermal denaturation curves were fit to a sigmoidal model for the calculation of an approximate apparent T*^m* for all mutants as previously reported[44].

3.5.0.16 Structural Representation of DHFR All images of the DHFR structure were prepared with UCSF Chimera, and volumetric representations were prepared using the MSMS package[45]. 4 crystal structures of DHFR (1RX1, 3QL3, 1RX4, and 1RX5) representing different states in DHFR's catalytic cycle were downloaded from PDB_REDO[46].

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4 Altered Expression of Lon Protease Reshapes the Mutational Landscape of a Model Enzyme

4.1 Introduction

The tenet of protein sequence-structure-function relationships in biophysics is clearly useful for understanding mutational impacts on protein function, but it is also an incomplete understanding of protein function in native cellular environments. In **Chapter 3** (page 54), we attempted to examine how the mutational landscape of DHFR is shaped by intrinsic structural properties and constraints on function. In optimizing our selection assay to map the mutational landscape of DHFR, we observed that changes to extrinsic properties (e.g. DHFR expression level) and environmental factors (e.g. TYMS expression, media conditions) can tune the selection pressure and reshape the mutational landscape. Our selection under stringent conditions in minimal medium and with DHFR expressed at $\sim 10\%$ of the endogenous level revealed advantageous mutations not observed at higher expression levels. Thus, our experiments report on sequence-structure-function relationships that are further convoluted by environment. In **Chapter 3**, we initially considered only sequence-structure-function relationships. Under this view, the mutational landscape is something fixed and intrinsic, shaped by thermodynamic and structural constraints on a molecular function. Now, by examining how environmental factors shape the mutational impacts, we consider sequence-structure-function-environment relationships. With the consideration of environmental pressures, we can view the mutational landscape as something that can be purposefully modulated.

Many experiments such as genetic screens and reverse genetic screens have examined how

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changes to the cellular environment change phenotypes. These studies are powerful, but they often examine only a small number of variants that survive a selection experiment or they examine more coarse-grained changes such as gene deletions. Even careful experiments to follow-up on large library screens are generally limited to a handful of mutations due to low experimental throughput. Therefore, we sought to advance our understanding of how changes to the cellular environment reshape sequence-function relationships by quantifying a large mutational landscape (thousands of mutations) before and after modulating a key cellular factor.

In this chapter, we repeated our optimized DMS assay for DHFR from **Chapter 3** with a perturbation to a key component of protein homeostasis in the selection strain. We then examined how this perturbation impacted the population of advantageous mutations from **Chapter 3** by examining changes in the distribution of selection coefficient, changes in the general mutational response at a position, and changes in expression level. Finally, we examined how well the *in vitro* measurements recapitulated the measurements from the *in vivo* selection assay.

4.2 Background

The protein-structure-function paradigm is overly simplistic because it ignores the complex environment that proteins fold in and the competing kinetic processes along the folding pathway. From the synthesis of the nascent peptide chain, the alternative pathways of unfolding, misfolding, aggregation, and degradation can shunt expressed protein away from the native fold[1, 2].

4.2.1 Protein Homeostasis in Cells

Cells have evolved complex protein quality control machinery to recycle non-native proteins by refolding or degradation. Accordingly, the two major components of protein quality control

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machinery are chaperones and proteases. Chaperones intervene at every possible stage of a protein's life — from nascent chain to misfolding under stress conditions — to restore the native fold of a protein. Certain chaperones can act passively (e.g. DnaJK, Trigger Factor) or utilize ATP as they unfold and refold proteins (e.g. Hsp90, GroEL, MmCpn). Proteases cleave peptide chains, and proteases with a role in degradation (e.g. Lon, ClpXP) recycle the constituent amino acids of a protein. This can also occur at many different stages in the lifetime of a protein, including degradation during stalled translation and degradation of protein aggregates.

4.2.2 Interplay between Protein Homeostasis in Cells and Protein Function

Seminal studies have examined the role of protein chaperones on mutational impacts observed at the cellular level. As one example, Hsp90 has been shown to buffer mutational impacts in a wide range of eukaryotic organisms, serving as a buffer of mutational impact and a capacitor for phenotypic variation[3–6]. Additionally, GroEL overexpression has been demonstrated to dampen the stability penalty against mutations during directed evolution [7, 8]. Using a model selection experiment, sequences with \sim 10-fold higher catalytic efficiencies were obtained with GroEL overexpression compared to selection with basal GroEL expression. Furthermore, endogenous GroEL expression levels have been shown to be linked to the rate of genetic diversification[9]. Notably, none of the studies we identified focused on the role of degradation machinery with the exception of studies interrogating the role of Lon protease in changing tolerance to genetic diversification [10–12], and no study examined if the perturbations to protein quality control cause identifiable patterns within the changes in an exhaustively mapped mutational landscape.

4.2.3 Lon Protease

Lon protease is a hexameric AAA+ ATP-dependent serine-protease that is responsible for degrading misfolded proteins. Lon is broadly conserved in all domains of life and is critical for mitochondrial function in higher organisms. In *E. coli*, Lon has a specific role in the cell cycle for degrading the checkpoint inhibitor SulA[13], but it is not generally believed to behave in a client specific manner[14, 15]. Rather, Lon has been demonstrated to bind and degrade proteins with exposed hydrophobic patches. Lon can be targeted with recombinant fusion tags of hydrophobic amino acids or by specific regulatory tags in some organisms[14], such as the ssrA tag that is fused to peptides stalled in translation[16]. Moreover, Lon had previously been implicated in degrading unstable DHFR variants in *E. coli*[1, 17], and deleting Lon in an MG1655 strain of *E. coli* masked the deleterious impact of 2 destabilizing mutations out of a panel of 21 mutants tested in growth experiments[17]. As with our competitive growth experiments (**Chapter 3.5.0.4**, page 110), these experiments were performed in minimal medium at 30° C.

4.2.3.1 B-strain *E. coli* Lon was identified in genetic screens of K12 *E. coli* because Lon depletion results in the inhibition of septation and cell division after exposure to UV radiation. When Lon is not present to degrade the checkpoint inhibitor SulA after exposure, exposed cells remain in an extended quiescent state[13]. This molecular mechanism was ultimately found to be the driver for the UV sensitivity of B strain *E. coli*, which are naturally deficient in Lon.[18] Furthermore, due to this deficiency in protein degradation machinery, B strain *E. coli* have been used for heterologous expression (e.g. BL21 cells), for many directed evolution experiments, and for the adaptation experiments of the *E. coli* Long Term Evolution Experiment (LTEE)[19–22]. Furthermore, our selection strain[23] is a B strain of *E. coli* that is naturally deficient in Lon protease [14, 15, 24] due to an insertion of IS186 in the *lon* promoter region[18].

Figure 4.1: Change in DHFR mutant dependent growth rates in the selection strain and a selection strain with a restored endogenous Lon promoter. The difference in growth rates from plate reader experiments (see Methods, **Chapter 3.5.0.4**, page 110) for ER2566 Δ *folA*/ Δ *thyA* with and without the endogenous Lon promoter over a panel of 11 DHFR variant (labels, top) are plotted as bars. The error bars represent the sum of errors for growth rates in the two cell lines, where error is calculated as the standard deviation over 8 independent experiments.

4.3 Results

To understand the origins of the counter-intuitive preference for mutation that we observed in DMS on DHFR (**Chapter 3.3.6.1**, page 86), we identified Lon as a cellular factor that potentially affects our mutational landscape for DHFR. To test the hypothesis that the permissive DHFR mutational landscape for DHFR can be made more restrictive with increased penalties against destabilizing mutations through expression of Lon protease, we performed a DMS over all single point mutants of DHFR in a variant of our selection strain that constitutively expresses Lon.

4.3.1 Generating a Lon-expressing Selection Strain

To test the impact of Lon expression on the mutational landscape of DHFR, we aimed to generate a variant of the ER2566 Δ *folA*/ Δ *thyA* selection strain that had expression levels of Lon that were similar to those for Lon in K12 *E. coli*. To change the expression level of Lon, we aimed to reverse the IS186 insertion in the Lon promoter and restore the native Lon promoter.

Figure 4.2: Change relative to WT in DHFR mutant-dependent growth rates in the selection strain and a selection strain with a restored endogenous Lon promoter. The difference in growth rates from plate reader experiments (see **Figure 4.1**, page 136) for ER2566 Δ folA $/\Delta$ thyA with and without the endogenous Lon promoter over a panel of 11 DHFR variant (labels, top) and normalized to the change in growth rate for WT DHFR are plotted as bars. The error bars represent the sum of errors for growth rates in the two cell lines, where error is calculated as the standard deviation over 8 independent experiments.

4.3.1.1 Reversing the IS186 Insertion by Restoring the Native Promoter Using Lambda Red recombination (see **Methods**, **Chapter 4.5.0.1**, page 163) we first generated a counter-selectable ER2566 Δf olA $/\Delta t$ hyA strain with a Kan-SacB selection/counter-selection cassette replacing the region upstream of Lon that contains the promoter. In a second round of Lambda Red recombination, we replaced the counter selectable marker with the native genome sequence for the region upstream of Lon protease.

In both selection and counter selection steps, colonies were first screened on the selection plates and then checked with colony PCR using primers that bind 50 bp upstream and downstream of the re-inserted region. When amplified from the *E. coli* circular chromosome with primers for the C-terminus of the ClpXP gene and the N-terminus of Lon, the Kan-SacB cassette is \sim 3 kb, the B-strain Lon promoter with the IS186 insertion is \sim 1.5 kb, and the K12-strain Lon promoter is 250 bp. These size differences allows all three constructs to be identified on a gel. PCR products from positive hits were then sequenced using the same forward and reverse primers from amplification to check for scarring at the recombination sites.

We then tested our re-engineered selection strain for expression of Lon protease. In Western blots of with anti-Lon antibodies, we did not see differences in Lon expression between our selection strain, the engineered $+$ Lon strain, and a K-12 positive control (unpublished data). These results were further compounded by problems with a poor-affinity primary antibody. Importantly, plate reader growth experiments (see **Methods**, **Chapter 3.5.0.4**, page 110) with 11 DHFR variants did not show a difference in growth rates between the two cell lines (**Figure 4.1**, page 136). Compared to the change in the growth rate with the new cellular background for WT DHFR, the change in the growth rate for the 11 DHFR variants was within error of 0.0 for all but 3 (**Figure 4.2**, page 137). From this, we concluded that restoring the endogenous promoter would not measurably change selection pressure in the selection assay.

4.3.1.2 Reversing the IS186 Insertion with a Constitutive Promoter Because Lon is reported to be a heat-shock protein[25], we hypothesized that its expression under the endogenous promoter would be repressed at the selection temperature of 30° C. To generate selection conditions that would measure the impact of Lon expression on the mutational landscape, we aimed to engineer a ER2566 Δ *folA*/ Δ *thyA* selection strain variant with Lon constitutively expressed at a level that is consistent with heat-shock in *E. coli*. Using Lambda Red recombination (see **Methods**, **Chapter 4.5.0.1**, page 163), we generated two ER2566 Δ *folA*/ Δ *thyA* selection strains with Lon expressed under the Anderson Set consensus promoter[26]. One construct has the native Lon RBS and one has an engineered RBS predicted by the Salis Lab RBS Calculator[27, 28]. We performed an anti-Lon western blot on lysate from multiple cell lines grown at 30° C and 42° C (**Figure 4.3**, page 139). Although the polyclonal antibody showed multiple bands, we observed a band at the expected molecular weight for the Lon monomer, and the additional bands could be labeling of degradation products. Overall, we saw a marked increase in Lon expression relative to B-strain

Figure 4.3: Expression of Lon under a constitutive promoter in the re-engineered selection strain. The expession level of Lon was observed by anti-Lon western blot for multiple strains of *E. coli*. Lane identities are marked by a growth temperature (bottom) and a number (top): **1)** Ladder, **2)** engineered selection strain with constitutive Lon promoter, **3)** engineered selection strain with constitutive Lon promoter and optimized RBS (ER2566 *folA*/*thyA* +Lon), **4)** ER2566 *folA*/*thyA* –Lon, **5)** B-strain BL21, **6)** K12 strain Top 10, see **Table 5.1**, page 174. Molecular weights to the ladder markers (labels left) and molecular identities (labels right) are indicated in label text.

negative controls for our re-engineered $+$ Lon selection strain and for a K12 strain positive control. We observed that the expression of Lon at 30° C with the constitutive promoter was qualitatively similar to endogenous Lon expression in a $K12$ strain under heat shock at 42° C. Furthermore, plate reader growth experiments showed a significant deleterious growth impact from Lon expression on a series of DHFR point mutants with multiple advantageous mutations (**Figure 4.4**, page 140). The impact of Lon on growth rates was generally of a greater magnitude with point mutants of DHFR as compared to WT (**Figure 4.5**, page 140). From this, we concluded that selection in our engineered $+$ Lon selection strain would display measurable changes on the mutational landscape resulting from Lon expression.

Figure 4.4: Change in DHFR mutant-dependent growth rates in the selection strain \pm Lon. The difference in growth rates from plate reader experiments (see **Methods**, **Chapter 3.5.0.4**, page 110) for ER2566 *folA*/*thyA ±*Lon over a panel of 18 DHFR variant (labels, top) are plotted as bars. The error bars represent the sum of errors for growth rates in the two cell lines, where error is calculated as the standard deviation over 8 independent experiments.

Figure 4.5: Change relative to WT in DHFR mutant-dependent growth rates in the selection strain *±* Lon. The difference in growth rates from plate reader experiments (see Figure 4.1, page 136) for ER2566 Δ folA/ Δ thyA *±*Lon over a panel of 18 DHFR variant (labels, top) and normalized to the change in growth rate for WT DHFR are plotted as bars. The error bars represent the sum of errors for growth rates in the two cell lines, where error is calculated as the standard deviation over 8 independent experiments.

Figure 4.6: Quality of the selection under +Lon conditions. **A)** Comparison of all pairwise replicates for +Lon selection coefficients from triplicate deep mutational scanning on DHFR. The Pearson correlation R^2 value from linear regression was 0.70. **B)** Distribution of standard errors for individual +Lon selection coefficients from a single replicate. Selection coefficients are the slope from a linear regression of allele frequency as a function of time in selection. The standard error here is the mean square of residuals. **C)** Distribution of standard deviations of selection coefficients for individual point mutants over replicate experiments. Each mutant had a measured selection coefficient in at least 2 of the 3 replicates.

4.3.2 Repeating Selection with a Lon-expressing Strain

To test this prediction about Lon's impact on the mutational landscape, we then repeated deep mutational scanning in biological triplicate (see **Methods**, **Chapter 3.5.0.6**, page 111). We refer to the two regimes as +Lon (**Chapter 4**) and –Lon (**Chapter 3**) selection.

4.3.2.1 Analyzing Noise in Selection Coecients The quality of +Lon selection (**Figure 4.6**, page 141) was comparable to that of $-L$ on selection(see Figure 3.29, page 88). The R^2 value between biological replicates was 0.79 and the median standard deviation between biological

Figure 4.7: Relationship between error and selection coefficient for +Lon selection. **A**) Standard deviation of selection coefficients over biological replicates. The data were plotted as a function of a sliding window over all single point mutants sorted by selection coefficient. Each point represents the mean error (biological replicate standard deviation) over 50 consecutive selection coefficients (after sorting by value) and the error bars represent *±*1 standard deviation of the error. The dashed line represents median error over the entire dataset, which was used determine the for WT-like behavior in **Figure 3.30A** (page 89). The dotted line represents $y = x$ for comparison between the magnitude of the error relative to the magnitude of the selection coefficient. **B**) Standard deviation over synonymous codons coding for the same sequence, plotted as in A.

replicates was 0.14. The error in the assay (**Figure 4.7**, page 142) also behaved similarly to that for $-$ Lon selection (see **Figure 3.31**, page 90) as a function of selection coefficient. Because the quality metrics were better for $+$ Lon selection, we kept the thresholds for advantageous and disadvantageous mutations.

4.3.3 Population-level Mutational Analysis of Selection Data

We then analyzed the change in selection with Lon expression using multiple metrics. Consistent with our hypothesis about the impact of Lon, we observed that the number of advantageous mutations after reintroducing Lon decreased from 737 in –Lon selection to 384 in +Lon selection. We also observed a selective decrease in the population of advantageous mutations and subsequent increase in the number of disadvantageous mutations (**Figure 4.8C**, page 143). When we compare selection coefficients for selection \pm Lon, we see a consistent pattern that selection coefficients are lower in selection with Lon, meaning that more mutations are disfavored relative

Figure 4.8: Lon protease expression reshapes the mutational landscape. **A)** Histogram of selection coefficients for mutations (top) in -Lon (grey) and $+$ Lon selection (green). The difference of the histograms (bottom) is shown with grey indicating more mutants for -Lon selection and green indicating more mutants for +Lon selection. The threshold for classification for advantageous and disadvantageous mutations is as in Figure 1 and indicated with dashed lines. **B)** Distribution of mutations classified by selection coefficients: $0.2 \leq$ advantageous (adv.), $0.2 > \text{WT-like} > -0.2, -0.2 \geq \text{disadvantageous (disadv.), null, and no data (a mutant was not detected in the$ library after transformation into the selection strain). Grey bars: –Lon selection; green bars: +Lon selection. **C)** Distribution of sequence positions into the 5 mutational response categories: Beneficial, Tolerant, Mixed, Deleterious, Intolerant. Grey bars: –Lon selection; green bars: +Lon selection. **D)** Heatmap of DHFR selection coefficients in the -Lon and $+$ Lon strains, showing details of the distributions shown in C) (dotted border). Positions (rows) are grouped by their mutational response category for $-L$ on and $+L$ on as in C) and sorted by the wild-type amino acid. Amino acid residues (columns) are organized by physiochemical similarity and indicated by their one-letter amino acid code. An asterisk indicates a stop codon. Advantageous mutations are shown in shades of red, disadvantageous mutations in shades of blue, Null mutations in grey and "No data" as defined in A) in black. Wild-type amino acid residues are outlined in black.

Figure 4.9: Comparison of selection coefficients \pm Lon. **A**) Scatterplot comparing selection coefficients in -Lon and +Lon selection, showing that mutations are generally repressed by Lon activity. Despite this general trend, we note that some top advantageous mutations are not impacted by Lon activity. **B)** Boxplot showing the distribution of wild-type amino acid residue rankings for –Lon (grey) and +Lon (green) selection. The wild-type amino acid residue ranking at each position is also shown as a distribution of points. Box plots show the median (orange bar) and upper/lower quartiles. The median wild-type amino acid residue rank is 8 for –Lon selection and 5 for +Lon selection. **C)** Wild-type amino acid residue rankings from –Lon selection plotted against wild-type amino acid residue rankings from +Lon selection. Dashed lines show *±*1 standard deviation for the change in rank between –Lon and +Lon selection.

to wild type (**Figure 4.9A**, page 144). These largest impacts are seen for mutations that are disadvantageous in both selection experiments, but the vast majority number of mutations that are advantageous in –Lon selection negatively impacted by Lon expression. In total, the mean selection coefficient for advantageous mutations decreased from 0.47 to 0.37, and the rank of the wild-type sequence increased by 340 to 865th. Finally, the median rank of the wild-type residue over all positions decreased from 8 in –Lon selection to 5 in +Lon selection (**Figure 4.9BC**, page 144).

4.3.4 Categorizing Positions by Mutational Impact and Position-based Analysis

The variability in the rank of the wild-type amino acid lead us to ask if there were patterns in the general mutational responses of different position. To examine in more detail how the mutational response of individual residues changes between selection *±*Lon, we used a K-means clustering algorithm (see **Methods**, **Chapter 4.5.0.3**, page 164) to group all DHFR sequence positions into 5 categories: positions where mutations were generally advantageous (Beneficial), generally WTlike (Tolerant), variably advantageous and disadvantageous (Mixed), generally disadvantageous (Restricted), and generally null (Intolerant). Grouping was performed separately for –Lon and +Lon selection (**Figure 4.8CD**, page 143 **Table 4.1**, page 146). Comparing the distributions of DHFR positions in $-L$ on and $+$ Lon conditions illustrates the extensive reshaping of the mutational landscape by Lon. For –Lon selection, 28 positions (17.6%) were classified as Beneficial, where nearly every mutation was preferred over the wild-type residue. In comparison, the number of Beneficial positions decreased to 10 in $+$ Lon selection, with only 3 surface-exposed positions (E48, T68, D127) common between the two Beneficial sets (**Figure 4.8D**, page 143, **Table 4.1**, page 146). Simultaneously, the number of Restricted positions increased from 42 to 67 with the reintroduction of Lon into the selection strain. The number of intolerant positions remained largely the same as many mutations are to deleterious for selection coefficient to be measured in either condition. These results support the conclusion that Lon activity broadly penalizes mutations, including a large subset of the advantageous mutations. Overall, the changes upon modulating Lon activity lead to a model in which upregulating Lon increases constraints on DHFR, and the mutational landscape changes from being permissive when Lon is absent to being more restricted when Lon is present.

4.3.5 Lon Impact as Selection Coecient

To analyze the constraints imposed by Lon on the DHFR mutational landscape in structural detail, we defined a Δ selection coefficient for each amino acid residue at each position as the difference between the $+$ Lon and $-$ Lon selections **(Figure 4.10A**, page 147). The Δ selection coefficient values were most negative at positions in the Beneficial category and at positions with a native

Table 4.1: Mutational response category and burial classification for DHFR positions. Positions are classified into mutational response categories of Beneficial ("B"), Tolerant ("T"), Mixed ("M"), Deleterious ("D"), and Intolerant ("I") for both –Lon and +Lon selection as described in **Methods** (**Chapter 4.5.0.3**, page 164). Positions are categorized in burial states of buried ("b") and exposed ("e") based on Getarea server calculations as described in **Methods** (**Chapter 4.5.0.4**, page 165).

	Lon			Lon				Lon				Lon			
Pos.	$\overline{}$	$+$	burial	Pos.	$\qquad \qquad -$	$+$	burial	Pos.	$\overline{}$	$\overline{+}$	burial	Pos.	$\qquad \qquad -$	$^{+}$	burial
1	L	T	b	41	D	D	$\mathsf b$	81	D	I	b	121	D	D	b
2	I	T	b	42	D	D	b	82	M	D	e	122	D	D	e
3	D	D	b	43	T	L	b	83	T	M	e	123	D	D	e
4	D	D	b	44	M	M	b	84	M	M	b	124	M	M	е
5	D	D	b	45	M	M	е	85	B	D	b	125	D	I	b
$\boldsymbol{6}$	D	D	b	46	L	L	b	86	B	Τ	e	126	B	D	b
$\overline{7}$	D	D	b	47	Β	M	b	87	T	M	e	127	B	B	e
8	D	D	b	48	Β	B	e	88	B	Τ	e	128	M	D	b
9	D	D	b	49	D	D	b	89	M	Τ	e	129	B	M	e
10	D	D	e	50	D	D	b	90	D	D	b	130	B	T	е
11	М	M	e	51	M	Τ	e	91	M	D	b	131	М	D	e
12	M	M	e	52	Τ	B	e	92	M	D	b	132	B	M	e
13	D	D	b	53	M	B	e	93	D	\mathbf{I}	b	133	D	T	b
14	T	D	b	54	D	D	b	94	D	\mathbf{I}	b	134	B	T	e
15	L	\mathbf{I}	b	55	Τ	B	e	95	I	\mathbf{I}	b	135	B	M	е
16	D	D	е	56	M	T	e	96	L	l	e	136	т	Τ	e
17	D	D	e	57	L	D	b	97	D	D	b	137	B	M	e
18	M	D	e	58	M	T	e	98	D	D	e	138	M	M	e
19	M	M	e	59	M	M	b	99	D	D	b	139	Τ	D	е
20	D	D	b	60	M	D	b	100	D	D	b	140	B	M	e
21	D	D	b	61	D	L	b	101	M	M	e	141	М	D	e
22	L	T	b	62	M	D	b	102	B	D	e	142	B	Τ	e
23	М	D	e	63	M	D	b	103	M	D	b	143	Τ	T	e
24	M	M	b	64	M	B	e	104	I	I	b	144	M	D	e
25	M	\top	e	65	M	B	e	105	\top	Τ	e	145	Τ	T	e
26	D	D	e	66	M	M	e	106	M	M	b	146	Τ	M	е
27	L	\mathbf{I}	b	67	M	B	е	107	L	I	b	147	D	D	b
28	D	D	e	68	B	B	e	108	T	M	e	148	D	D	e
29	D	D	e	69	M	M	b	109	M	M	b	149	D	D	e
30	B	M	b	70	Τ	B	e	110	D	I	b	150	M	D	е
31	D	D	e	71	M	M	e	111	M	D	b	151	M	D	е
32	D	D	e	72	B	M	b	112	M	I	b	152	B	M	b
33	M	M	е	73	M	M	е	113	L	I	b	153	M	D	b
34	M	D	b	74	M	D	b	114	B	M	e	154	B	M	b
35	L	T	b	75	M	M	b	115	M	D	b	155	M	D	b
36	M	M	е	76	M	M	e	116	B	M	b	156	M	D	b
37	M	M	е	77	Β	M	е	117	D	D	b	157	M	M	e
38	Μ	D	e	78	B	M	b	118	B	D	e	158	Τ	D	e
39	M	M	b	79	M	M	е	119	M	M	e	159	B	Τ	$\mathsf{e}% _{t}\left(t\right)$
40	M	$\mathsf D$	b	80	M	M	e	120	B	M	e				

Figure 4.10: \triangle selection coefficients show Lon impact. **A)** Conceptual diagram of \triangle selection coefficients, calculated as the +Lon selection coefficient minus the -Lon selection coefficient (see Methods, Chapter 3.5.0.10, 115). **B)** Heatmap of Δ selection coefficient values for all positions not classified as Intolerant. Δ selection coefficients values between -0.2 and 0.2 are shown in white; Δ selection coefficients >0.2 are in shades of red and Δ selection coefficients \lt -0.2 in shades of blue. Amino acid residues (columns) are organized by physiochemical similarity and indicated by their one-letter amino acid code. The mean Δ selection coefficient (avg) at each position is shown as a separate column and outlined with a light blue box. Positions (rows) are sorted by the wild-type amino acid and grouped by their mutational response category from the –Lon selection in **Figure 4.8CD** (page, 143). Positions with a native VILMWF or Y amino acid are indicated with an orange bar to the left. **C)** Per-position mean Δ selection coefficient displayed on the structural model of DHFR. The 5 cross-section slices of the DHFR structure are displayed as in **Figure 3.30C** (page, 89), and the color scale is as in B).

Figure 4.11: Δ selection coefficients show Lon impact on natively buried and hydrophobic residues. **A)** Histogram of Δ selection coefficients (top) with mutants at positions with hydrophobic (AVILMWFY) wild-type amino acid residues in orange and at positions with polar (HKRSTNQDE) wild-type amino acid residues in grey. Selection coefficients for positions with a wild-type P, G, or C residue are not included. The difference of the histograms (bottom) is shown with grey indicating more mutants to positions with a wild-type polar residue and orange indicating more mutants to positions with a wild-type hydrophobic residue. Dotted lines indicate twice the median of standard deviations from (**Figure 3.30B**, page 89). **B)** Histogram of Δ selection coefficients (top) with mutants at buried positions (solid) and at exposed positions (hatched) as listed in Table S4. Selection coefficients for positions that were Intolerant in -Lon selection are not included. The difference of the histograms (bottom) is shown with solid indicating more mutants to buried positions and hatched indicating more mutants to exposed positions.

VILMWF or Y amino acid residue (**Figure 4.10B**, page 147). This pattern for deleterious is most measurable in the Mixed category. This pattern is also clearly observed in the Deleterious category, except that it is not readily measurable because many mutations go from being disadvantageous to null. Notably, most mutations to Tolerant positions do not have Δ selection coefficient with large magnitudes. When we analyze over the whole dataset of Δ selection coefficients, mutations at positions with native hydrophobic residues are enriched for negative Δ selection coefficients **(Figure 4.11**, page 148). Strikingly, the mean Δ selection coefficient was –0.71 for the 65 buried positions with $< 20\%$ side-chain solvent accessible surface area, compared to -0.27 for the 79 exposed positions (see **Table 4.1**, page 146). This may explain, in part, why the Tolerant positions are not greatly impacted by Lon. This result is also visible on the DHFR structure, which makes it clear that many of the buried residues that are not impacted by Lon are the residues that are in the active site and are already classified as Deleterious or Intolerant (**Figure 4.10C**, page 147). These results show that Lon has a broad impact on the mutational landscape throughout the DHFR structure but imposes particularly strong constraints in the DHFR core.

4.3.5.1 Correlation between Selection Coecient and *T^M* Moreover and as expected, the Δ selection coefficients between +Lon and -Lon selection are correlated with T_m , except for mutations near the active site (Figure 4.12, page 150). Strikingly, when we compare different mutations at the same position, the change in Δ selection coefficients (i.e. Lon sensitivity) correlates with the change in T*^m* values. These results indicate that the selected advantageous mutations are typically destabilizing, and that destabilization is correlated with Lon sensitivity. One possible explanation for the selection advantage of destabilizing mutations that have an increase in velocity (e.g. L24V, W30F/M, M42F/Y, H114V, D116I/M, E154V) is that these mutations promote breathing motions that accelerate product release, which is rate limiting for

Figure 4.12: Correlation of Δ selection coefficients to T_m . **A)** Correlation between *in vitro* T_m values and *in vivo* Aselection coefficients for DHFR wild-type and characterized mutants. Each point represents a single point mutations (see **Table 3.8**, page 100). Points are colored colored according to the position's location in the DHFR structure: core (purple), surface beta-sheet (gold), proximal to the adenine ring on NADPH (blue), or proximal to the active site and M20 loop (red). G) ΔT_m values and $\Delta\Delta$ selection coefficient for mutations at the same position. Points representing comparison between mutants are numbered as follows: **1)** D116I-M, **2)** M42Y-F, **3)** W30M-F, **4)** I91G-A, **5)** Q102W-L, **6)** L62A-V, **7)** I41A-V, **8)** W47V-L.

wild-type DHFR at neutral pH[29] and for a hyperactive DHFR mutant with a 7-fold increase in k*cat*[30].

4.3.5.2 Lon Expression Decreases *In Vivo* **Expression of DHFR** To examine the impact of Lon further, we measured the soluble expression in ER2566 Δ folA/ Δ thyA +Lon cells (see **Methods**, **Chapter 3.5.0.14**, page 122, **Table 4.2**, page 151) Importantly, expression measurably decreased for all mutants in the presence of Lon (**Figure 4.13A**, page 152). Furthermore, the change in expression level has moderate correlation with the change in selection coefficient between the two regimes (Figure 4.13B, page 152). While these data are not sufficient to support a direct interaction between DHFR and Lon, we can conclude that Lon can suppress a broad range of mutations with multiple mechanisms underlying their advantageous selection impact.

Table 4.2: Soluble DHFR abundance levels in molecules per cell. Abundances were measured from lysate activity assays as described in **Methods** (**Chapter 3.5.0.14**, page 122). All values are for the SMT205 plasmid transformed into the ER2566 Δ *folA*/ Δ *thyA* +Lon. NM, not measured.

Variant	Molecules per cell	Standard deviation
WT	71.4	23.9
L24V	65.5	13.4
W30F	79.0	9.3
W30M	63.7	11.0
141A	9.2	8.4
141V	218.9	108.5
M42F	290.6	5.9
M42Y	162.3	4.9
H45S	69.6	13.8
W47L	349.2	46.7
W47V	NM	NM
L62A	NM	NM
L62V	104.7	15.3
C85L	63.6	2.6
191A	56.0	14.5
191G	86.8	20.7
R98Y	161.5	29.4
Q102L	198.4	57.5
Q102W	133.1	27.6
T113V	212.2	27.5
H114V	NM	NM
D116I	NM	NΜ
D116M	46.5	7.0
E154V	36.2	0.8
L156Y	44.8	6.6

Figure 4.13: Correlation of Δ selection coefficients to change in cellular abundance \pm Lon. **A)** DHFR cellular abundance calculated from the lysate DHFR activity and *in vitro* kinetics with purified enzyme (see **Methods**, **Chapter 3.5.0.13**, page 121). Error bars represent the cumulative percent error (standard deviation) from three independent experiments for velocity and three biological replicates for lysate activity. Data are shown in both the -Lon (light grey) and +Lon (green) conditions. **B)** Correlation between the ratio of cellular DHFR abundance in A) and *in vivo* Δ selection coefficients \pm Lon for DHFR wild-type and point mutants. Each point represents a mutation and is colored according to the position's location in the DHFR structure: core (purple), surface beta-sheet (gold), proximal to the adenine ring on NADPH (blue), or proximal to the active site and M20 loop (red). X-axis error bars represent the cumulative percent error (standard deviation) from three measurements of DHFR concentration with and without Lon (Methods). Y-axis error bars the cumulative error (standard deviation) from three biological replicates for selection with and without Lon (Methods).

4.3.6 Structural Patterns in DHFR Selection

Taken together, our data indicate that the observed widespread changes in the mutational landscape of DHFR can be explained by a penalty for destabilizing mutations from Lon expression, leading to extensive activity $-$ stability tradeoffs for advantageous mutations. The effect of these two selection pressures is directly observable in the structural arrangement of the mutational response categories. In –Lon conditions, mutational responses are arranged in shells around the hydride transfer site[31] (**Figure 4.14A**, page 153) where the proportion of advantageous mutations increases with increasing distance (**Figure 4.14B**, page 153, **Figure 4.15B**, page 154). This same spatial pattern also holds for +Lon selection (**Figure 4.14C**, page 153)., but it is now superimposed with the additional pressure against destabilizing mutations such that there are no Beneficial positions in the core(**Figure 4.16**, page 155). In contrast, the mutational responses as a function of distance to other DHFR sites (e.g. C5 of

Figure 4.14: Structural characterization of multiple constraints on the DHFR mutational landscape. **A)** Mutational response categories from –Lon selection (top, categories in **Figure 4.8CD**, page 143) and +Lon selection (bottom, categories as in **Figure 4.8CD**, page 143) colored onto residues and displayed on slices as in **Figure 3.30C** (page 89). **B)** Relationship between mutational response and distance from hydride transfer for –Lon selection. The percent of positions from each mutational response category are plotted as a function of distance from the site of hydride transfer. Each category colored as in A, top). **C)** Relationship between mutational response and distance from hydride transfer for +Lon selection. Each category colored as in A, bottom).

Figure 4.15: Selection coefficients under the two Lon expression regimes mapped on the DHFR structure. Structural model of DHFR (PDB ID: 3QL3) in ribbon representation with the DHF substrate and the NADPH cofactor represented by spheres (yellow carbon and heteroatom coloring). The residues are colored in **A,B)** by mutational response category from **Figure 4.8CD** (page 143) for –Lon selection, in **C,D)** by mutational response category from Figure 4.8CD (page 143) for +Lon selection, or in E, F) by the per-position mean Δ selection coefficient from Figure 4.10 (page 147).

Figure 4.16: Burial of residues within each mutation response category reported as the mean number of atomic neighbors. Each point represents one amino acid side chain, and the y-axis reports the average number of heavy atom neighbors within an 8 Å shell for all heavy atoms in that side chain. Box plots are overlaid on the distribution to show the median (orange bar) and upper/lower quartiles. Mutational response categories are shown for both –Lon and +Lon selection. The green arrow highlights the absence of buried Beneficial positions in +Lon selection.

the NADPH adenine ring) do not show as strong of a relationship (**Figure 4.17**, page 156). These findings illustrate how the contributions from two constraints – one structural (distance from hydride transfer) and one dependent on cellular context (Lon) – can be distinguished in structural patterns in the mutational landscape.

4.3.7 Comparing Sequence Preferences in Selection and Evolution

We then asked how constraints in our assay compare to the constraints that have shaped natural DHFR sequences. We first examined the performance of the WT sequence in the selection assay. As mentioned previously, there are 737 advantageous mutation in –Lon selection and 384 advantageous mutation in $+$ Lon selection, and the median rank of the wild-type residue over all positions was 8 in –Lon selection and 5 in +Lon selection (**Figure 4.9**, page 144). Thus, the addition of Lon makes the WT sequence generally more favorable in selection. To further investigate how our selection assay recapitulates natural selection pressures, we used profile similarity metrics to (**Chapter 4.5.0.5**, page 165). Briefly, profile similarity is an informatics metric that quantifies the similarity of two distributions. When we look at the similarity of

Figure 4.17: Residues in mutational response categories in the –Lon selection as a function of distance from several sites in the DHFR structure. **A)** Location of hydride transfer site, the M20 residue on the M20 loop (orange), and hot spot sites from Figure 4 (the core of the globular domain represented by I41, the beta-sheet surface below the active site represented by L112, and the adenine ring on NADPH) indicated on the DHFR structure (PDB ID: 3QL3). **B-F)** The distance relationships between each site and the residues in each mutational response category in the –Lon selection are shown (left) as boxplots with points representing the individual mutants and (right) as curves showing the percent of sequence positions in each mutational response category as a function of distance from the site. Boxplots and curves are colored by mutational response categories from –Lon selection as in **Figure 4.14** (page 153).

Figure 4.18: Comparison of DHFR per-position sequence preferences. **A)** Profile similarity (see Methods) was calculated to compare the per-position distribution of amino acid frequencies between selection *±*Lon (blue), between –Lon selection and an MSA of DHFR orthologues (grey), and between +Lon selection and the MSA. Each point represents a single position in DHFR. A profile similarity value of 1.0 indicates identical distributions at that position, and a value of 0 represents no overlap in the distributions. The box plot shows the median (orange line), the interval between the first and third quartiles (box), and the maximum and minimum (whiskers). **B)** Scatterplot comparing the similarity of amino acid preferences in the MSA to selection *±*Lon. Each dot represents a single position in the DHFR sequence. X-axis values represent the profile similarity score between the MSA and –Lon selection for amino acid preferences at each position. Y-axis values represent the profile similarity score between the MSA and $+$ Lon selection for amino acid preferences at each position. The grey dashed lines represent $y = x \pm$ one standard deviation for $|\text{Similarity}(-\text{Lon vs. MSA})\text{position} - \text{Similarity}(+\text{Lon}$ vs. MSA)position|. Positions in the green region have amino acid preferences more similar to the MSA for +Lon selection, and positions in the grey region have amino acid preferences more similar to the MSA for –Lon selection. **C)** Crystal structure model of DHFR (PDB ID: 3QL3) with positions colored by their location in the green, grey, and white regions from panel B).

tolerated amino acid distributions from selection *±*Lon and a MSA, we see that the addition of Lon expression into selection broadly improves similarity between the experiment and naturally observed DHFR sequences (**Figure 4.18**, page 157). As with WT rank, the addition of Lon to selection appears to reconcile about half of the differences between the assay selection pressure and natural selection pressure(s) as measured by these metrics, although the behavior of these metrics is non-linear. Therefore, we interpret this result as measurable, but incomplete improvement in recapitulating natural selection pressures. Furthermore, we can see that the improvements in the profile similarity and WT rank metrics are not localized, but broadly spread throughout the protein. These improvements are largely observed at buried positions, which is expected because the Δ selection coefficient values are largest at buried positions.

4.3.8 Examining the Lon Locus in *E. coli* **Genome from Seminal Experiments**

For the sake of hypothesis generation, we next asked what seminal experiments had been performed in B strain *E. coli*, and therefore might be impacted by Lon expression. Because we anticipated that the impact of Lon would be more obvious over long selection times, we examined the *E. coli* LTEE. A B-strain of *E. coli* was indeed used for the LTEE [19], and the published representative genome for the LTEE strain did indeed have the IS186 insertion into the Lon promoter[**?**]. Considering the lessons learned from the LTEE experiment about the rate and mechanism of adaptation in *E. coli*, this result opens questions about Lon's impact on how fast adaptation occurs, what pathways are accessible, and what adapted states are incompatible with more stringent protein quality control regimes.

4.4 Discussion

In this chapter, we examined how the cellular state of protein quality control can reshape the mutational landscape of DHFR by changing the penalties for destabilizing mutations. Selection on DHFR point mutants in the study illustrates how a structural constraint from hydride transfer can shape a mutational landscape and how an environmental constraint from Lon protease reshapes that landscape. The impact of structural and environmental constraints have been considered previously [32–38], and our work allows us to see how multiple constraints combine to create alternate mutational landscapes. In the results presented here, we observe distinct structural patterns arising from both constraints.

More can be learned about the basics of enzyme function by examining the rich mutational dataset we generated for DHFR. Metabolomics experiments with various mutants will help deconvolute changes in the kinetic properties of DHFR from changes in the cellular environment. Mechanistic studies on the origin of increased DHFR activity via stopped flow kinetics, NMR, and hydrogen-deuterium exchange mass spectroscopy (HDX) may reveal how the destabilization of different regions of the DHFR protein increases velocity by affecting different microscopic constants. These experiments may clarify why so many advantageous mutations are distal to the active site.

We can propose a mechanistic explanation for the spatial patterning within the mutational landscapes from this work. The positive mutations we characterized in this study showed moderate decreases in stability coupled with mild increases in turnover. Many of the observations can be explained if these destabilizing mutations allow access to excited conformational states. This kind of molecular mechanism for rate acceleration would be analogous to that observed in recent work by Hilser and colleagues for surface glycine mutations to *E. coli* adenylate kinase [39, 40].

The rate limiting step of DHFR is product release, which is coupled to the dynamics of the M20 loop that lies over the active site[29, 41]. Excited conformational states could promote faster conformational exchange in the M20 loop or potentially enable the hinge-like motions observed in the human DHFR orthologue and in "humanized" *E. coli* DHFR [42], both of which have a higher *kcat* than the wild-type. This would explain the observation that there are many positive mutations throughout the DHFR structure.

We also note here that the pattern of advantageous mutations throughout the protein is similar to the observation of many distal mutations becoming fixed in directed evolution. A number of directed evolution experiments have been performed in BL21 [43, 44], although many directed evolution projects use K12 strains or proprietary strains of *E. coli*. It could be informative to examine if the Lon expression in the selection strain changes the likelihood that destabilizing mutations are fixed during directed evolution and if the number of fixed mutations distal to the active site is decreased. Similarly, more detailed bioinformatics analysis may be able to detect evolutionary signal from Lon, but even the naïve analyses here support the conclusion that more stringent selection for stability makes selection more consistent with natural protein sequences. It remains to be seen if this is true in general or only for specific model systems and selection conditions. One potential caveat to this is that most endogenous enzyme expression or induced expression from a plasmid is much higher than tens of DHFR copies per cell that are expressed in our optimized selection conditions. It is possible that changes in client expression level may change the impact of Lon on the mutational landscape (i.e. over-saturating Lon).

We anticipate that mutational landscapes are subject to the interplay between different components of protein quality control. Our work allows us to consider the engineering potential in exploiting opposing pressures for precisely tuning mutations landscapes, where protease
activities add constraints and chaperones relieve them. To illustrate the engineering potential in tuning refolding and degradation activities, we will discuss seminal works about the impact on mutational landscapes from two different chaperones: GroEL and Hsp90. The first comparison is with Danny Tawfik and Nobu Tokuriki's use of GroEL overexpression to dampen activity-stability trade-offs during directed evolution $[8, 45]$. In that study using a model selection experiment, sequences with 10-fold higher activities were obtained with GroEL overexpression compared to selection with basal GroEL expression. If GroEL over-expression is generally useful for traversing through active but destabilizing regions of sequence space, Lon over-expression may also be useful in later polishing rounds of selection and may help identify active and well-behaved sequences. The second comparison is with Susan Lindquist and colleagues' study that showed deleterious phenotypes from mutations are buffered by Hsp90, a major chaperone in eukaryotic cells [3–6]. Considering their observations with Hsp90 and our observations with Lon, protein homeostasis appears to act as a set of antagonistic forces on mutational landscapes.

4.4.1 Discussion

We envision a general method of engineering landscapes to respond to external switches. The possibility of engineering mutational landscapes has not yet been explicitly considered to our knowledge. This work is a preliminary example of how a mutational landscape can be tuned along two dimensions: activity and stability, but we anticipate that many other tunable pressures will be identified. We anticipate that further study of antagonistic pressures on mutational landscapes will yield a new toolkit for the fine control of the mutational landscapes that guide movements through sequence space.

This concept could also be tested directly by performing proof of principle experiments using

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Figure 4.19: Concept for modulating the mutational landscape with Lon to combat antibiotic resistance. **A)** Resistance (orange) to an antibiotic mediated by a protein is a function of trade-offs between activity and stability (purple) in that protein. Resistance mutations arise in the population at the expense of stability. **B)** Resistance to an antibiotic is mediated as in A), but Lon protease expression is manipulated by a Lon inhibitor (grey) and a Lon agonist (green) in a time-dependent fashion. This manipulation of the mutational landscape causes over adaptation under permissive protein quality control and elimination of the resistant bacteria under stringent protein quality control.

directed evolution while gradually increasing Lon expression. These experiments are similar in concept to directed evolution with upregulated GroEL, and they could be combined with early expression of chaperones to allow the directed evolution experiment to more effectively search functional sequence space in early selection rounds and optimize for a well-folded, thermostable protein in later rounds. Directed evolution with titrated protein quality control is one example of the more general idea of applying the concept of engineering switchable behavior into the mutational landscape.

Another potential application for the principle of engineering entire mutational landscapes is combating antibiotic resistance (**Figure 4.19**, page 162). Antibiotic treatment could be combined with a Lon inhibitor, to incentivize pathogens to adapt via destabilizing mutations. Then, later in the time course, the Lon inhibitor would be replaced with a Lon agonist, strongly selecting against the pathogen. Further experimentation is needed to establish a proof of principle and to determine the optimal time-periods for the different phases of treatment.

4.5 Methods

4.5.0.1 Generation of ER2566 \triangle *folA* \triangle *thyA* + Lon The ER2566 \triangle *folA* $/\triangle$ *thyA* + Lon strain was generated from ER2566 Δ *folA*/ Δ *thyA* –Lon by lambda red recombination using Support Protocol I from Thomason et al. 2014[46]. The pSim6 plasmid bearing the Lamda red genes linked to a temperature sensitive promoter and the pIB279 plasmid bearing the Kan-SacB positive-negative selection marker[47] were gifts from Carol Gross. The Kan-SacB cassette was amplified with 2 rounds of PCR using primers with 5' homology arms for the region upstream of the Lon gene (**Table 5.3**, page 174). The insertion fragment containing the Anderson consensus promoter[26] with homology arms for the region upstream of Lon in the ER2566 genome was amplified from primers using overlap extension PCR.

4.5.0.2 Western Blot with anti-Lon Polyclonal Antibody Western blots to detect Lon expression were performed as described in **Chapter 2 – Methods** (**Chapter 3.5.0.11**, page 117), except that the lysate volume was calculated as (volume of culture for pellet) \times (OD600 of culture for pellet) \times (45 /muL Laemmli buffer), and 2 μ L (1:10,000) of polyclonal rabbit anti-Lon antibody (Biorbyte, cat $\#$ orb231326) was used as the secondary antibody.

4.5.0.3 Clustering of DHFR Positions by Mutational Response For clustering of positions, an inhouse Python script was used for K-means clustering of positions into categories based on general mutational response at a position (i.e discarding the amino acid identities of the mutants). Spatial clustering was performed based on selection coefficient with distance between two positions calculated in the following steps: 1) sorting the vectors of selection coefficients for each position, **2)** trimming the vectors to match vector lengths after discarding "no data" values, **3)** calculating a Δ vector by subtracting the two sorted and trimmed vectors, and finally calculating the distance as the mean of the absolute value of the Δ vector. For the first round, categories were seeded with virtual positions that have prototypical mutational profiles for the 5 categories (Beneficial, Tolerant, Mixed, Restricted, and Intolerant). From this first round, all positions in DHFR were categorized into initial clusters. In subsequent rounds, the virtual positions were removed and candidate positions were compared to the non-self positions populating each cluster. The distance between a candidate position and a cluster of positions is calculated as the average of the distance between the candidate position and the three closest non-self positions in the cluster. Clustering was performed over 10 rounds following the initial seeded round, and convergence was confirmed by observing that 5 repetitions gave identical clusters.

4.5.0.4 Structural Analysis of DHFR Selection The distance between the positions within each mutational response category and sites within the DHFR structure (hydride transfer site, M20 loop, core of the globular domain, and the beta-sheet surface beneath the active site) were determined using a model of the transition state provided by Phil Hanoian[31]. The representative atom for the hydride transfer site is the hydride atom in the transition state model. The representative atom for the adenine ring is C5 (C18 in the pdb). The representative atom for the core of the globular domain is the alpha carbon of I41. The representative atom for the beta sheet region is the alpha carbon of D114. For all cases, the distance is defined as the distance between the representative atom and the alpha carbon of the target position.

Mean atom neighbors for each residue on a structure were calculated using an in-house python script. The number of non-hydrogen atoms within an 8 Å shell of each non-hydrogen atom in the structure were counted and averaged for all non-hydrogen atoms at each side chain. These values we calculated for 4 crystal structures of DHFR (PDB IDs: 1RX1, 3QL3, 1RX4, 1RX5) and averaged over the set.

Solvent accessible surface accessible surface area (SASA) was calculated using the Getarea server[48] for 4 crystal structures of DHFR (1RX1, 3QL3, 1RX4, and 1RX5) representing different states in DHFR's catalytic cycle. For all positions in DHFR, if the residue had <20% SASA in any structure, the residue was classified as buried. All other residues were classified as exposed.

4.5.0.5 Profile Similarity Analysis We downloaded the DHFR alignment from OpenSeq.org[49], selected all bacterial DHFR sequences, and aligned the *E. coli* DHFR sequence to the MSA using MUSCLE[50]. Frequencies for each amino acid at each sequence position in the MSA were calculated from counts in each column, with absent amino acids given an arbitrarily low frequency of 0.0001. To compare the amino acid frequencies from the MSA to the selection coefficients, we multiplied the selection coefficients by -1 and back-calculated frequencies using Boltzmann weighting using a temperature (5.44 for –Lon selection, and 6.95 for +Lon selection) that resulted in the mean sequence entropy to be within *±*0.01 of that of the MSA (0.50). Then, profile similarity at each sequence position was calculated as 1 – the Jensen-Shannon Divergence of the amino acid frequencies. Profile similarity was determined over columns corresponding to positions 2-158 because the DHFR library begins at position 2 and the DHFR MSA cuts off after position 158.

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5 Appendix

Table 5.3: Primers

Table 5.5: Selection coefficients ±Lon.

	$-Lon$			$+$ Lon		
	Selection	Standard	Standard	Selection	Standard	Standard
Mutation	coefficient	deviation	error	coefficient	deviation	error
WT	0.0	0.0	0.0	0.0	0.0	0.0
M ₁ A	ND	ND	ND	ND	ND	ND
M ₁ C	ND	ND	ND	ND	ND	ND
M1D	ND	ND	ND	ND	ND	ND
M ₁ E	ND	ND	ND	ND	ND	ND
M1F	ND	ND	ND	ND	ND	ND
M1G	ND	ND	ND	ND	ND	ND
M1H	ND	ND	ND	ND	ND	ND.
M11	Null	nan	nan	Null	nan	nan
M1K	Null	nan	nan	Null	nan	nan
M1L	Null	nan	nan	Null	nan	nan
M1N	ND	ND	ND	ND	ND	ND
M1P	ND	ND	ND	ND	ND	ND
M1Q	ND	ND	ND	ND	ND	ND
M1R	Null	nan	nan	Null	nan	nan
M1S	ND	ND	ND	ND	ND	ND
M1T	Null	nan	nan	Null	nan	nan
M1V	Null	nan	nan	Null	nan	nan
M1W	ND	ND	ND	ND	ND	ND
M1Y	ND	ND	ND	ND	ND	ND
$M1*$	ND	ND	ND	ND	ND	ND
12A	Null	nan	nan	Null	nan	nan
I ₂ C	Null	nan	nan	Null	nan	nan

Table 5.6: *In vitro* DHFR reactions

		DHF concentration ([DHF]) and DHFR velocity (V)							
		[DHF]	V	[DHF]	V	[DHF]	V	[DHF]	v
variant	run	(μM)	(s^{-1})	(μM)	(s^{-1})	(μM)	(s^{-1})	(μM)	(s^{-1})
E154V	1	39.30	6.66	38.68	6.33	38.09	6.65	37.48	6.49
		36.93	6.53	36.30	6.94	35.72	6.75	35.11	6.81
		34.52	6.77	33.93	6.29	33.33	6.37	32.73	6.97
		32.14	6.97	31.56	6.41	30.99	6.49	30.39	6.98
		29.83	6.24	29.28	6.11	28.70	5.69	28.13	6.57
		27.58	6.20	27.04	6.70	26.51	6.46	25.97	5.63
		25.46	5.29	24.93	5.59	24.39	5.49	23.91	5.70
		23.40	5.22	22.90	6.07	22.40	5.48	21.92	5.12
		21.46	5.34	20.98	4.65	20.53	5.07	20.07	5.22
		19.63	4.98	19.18	5.14	18.74	4.99	18.32	5.00
		17.91	4.81	17.48	4.67	17.09	4.51	16.68	4.62
		16.28	4.21	15.91	4.37	15.52	4.06	15.14	3.86
		14.76	4.25	14.43	3.65	14.06	3.91	13.71	3.97
		13.39	3.71	13.05	3.39	12.73	3.45	12.41	3.74
		12.11	3.64	11.80	3.22	11.50	3.43	11.21	2.85
		10.92	3.07	10.63	3.08	10.35	2.90		
E154V	2	38.65	11.71	38.14	12.15	37.63	9.84	37.14	11.90
		36.63	11.73	36.13	10.96	35.65	10.79	35.10	12.29
		34.61	11.68	34.07	11.46	33.56	12.33	33.05	12.13
		32.54	11.86	32.03	11.83	31.52	11.73	31.02	12.61
		30.52	11.05	30.02	11.70	29.52	11.69	29.02	12.09
		28.54	10.99	28.05	12.38	27.55	10.89	27.05	11.24
		26.60	10.51	26.14	9.72	25.65	9.79	25.20	10.89
		24.74	10.20	24.27	10.24	23.82	10.79	23.39	10.59
		22.92	9.85	22.48	9.51	22.03	10.65	21.61	9.94
		21.19	10.30	20.76	9.02	20.34	10.64	19.90	8.11
		19.48	9.32	19.06	8.79	18.65	9.56	18.25	9.15
		17.84	9.29	17.45	9.16	17.06	8.96	16.67	9.13
		16.30	7.46	15.93	8.23	15.57	7.46	15.20	8.17
		14.85	7.68	14.49	8.44	14.15	7.01	13.81	8.11
		13.46	7.59	13.14	6.95	12.82	7.33	12.50	7.32
		12.20	6.62	11.89	7.39	11.58	6.13	11.28	7.14

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