Programming mRNA decay to modulate synthetic circuit resource allocation

Ophelia S. Venturelli1,2, Mika Tei1,2, Stefan Bauer3, Leanne Jade G. Chan4, Christopher J. Petzold4 & Adam P. Arkin1,2,3,5

Synthetic circuits embedded in host cells compete with cellular processes for limited intracellular resources. Here we show how funnelling of cellular resources, after global transcriptome degradation by the sequence-dependent endoribonuclease MazF, to a synthetic circuit can increase production. Target genes are protected from MazF activity by recoding the gene sequence to eliminate recognition sites, while preserving the amino acid sequence. The expression of a protected fluorescent reporter and flux of a high-value metabolite are significantly enhanced using this genome-scale control strategy. Proteomics measurements discover a host factor in need of protection to improve resource redistribution activity. A computational model demonstrates that the MazF mRNA-decay feedback loop enables proportional control of MazF in an optimal operating regime. Transcriptional profiling of MazF-induced cells elucidates the dynamic shifts in transcript abundance and discovers regulatory design elements. Altogether, our results suggest that manipulation of cellular resource allocation is a key control parameter for synthetic circuit design.

1 California Institute for Quantitative Biosciences, University of California Berkeley, Berkeley, California 94158, USA. 2 Department of Bioengineering, University of California Berkeley, Berkeley, California 94720, USA. 3 Energy Biosciences Institute, University of California Berkeley, Berkeley, California 94704, USA. 4 Joint BioEnergy Institute and Biological Systems and Engineering Division, Lawrence Berkeley National Laboratory, Berkeley, California 94720, USA. 5 Environmental Genomics and Systems Biology, Lawrence Berkeley National Laboratory, Berkeley, California 94720, USA. Correspondence and requests for materials should be addressed to O.S.V. (email: venturelli@wisc.edu) or to A.P.A. (email: aparkin@lbl.gov).
Engineered biological systems have diverse applications in medicine, bioenergy and agriculture\textsuperscript{1}. Novel cellular behaviours can be programmed by interacting networks of biomolecules to process information from the environment and execute target functions. These synthetic biomolecular circuits interact with endogenous cellular processes through competition over shared resources that include ribosomes, transfer RNAs (tRNAs), RNA polymerases, amino acids and nucleotides\textsuperscript{2,3}. Resource utilization influences the predictability, function and evolutionary stability of engineered networks and constrains the achievable parameter space for synthetic circuit design\textsuperscript{4}.

Cells operate with a limited resource quota, which manifests as a trade-off in the partitioning of energy between cellular processes and synthetic circuit functions\textsuperscript{1,3,5,6}. A core challenge is to rewire cellular regulation to optimally distribute resources between the host-cell and synthetic circuit processes. While there are numerous mechanisms to control target gene expression including engineered promoters\textsuperscript{7}, protein degradation\textsuperscript{8} or CRISPRi\textsuperscript{9–11}, limited technologies exist to globally redistribute and synthetic circuit functions\textsuperscript{1,3,5,6}. A core challenge is to rewire a trade-off in the partitioning of energy between cellular processes required for a target function, while downregulating competing pathways. MazF is a sequence-dependent and ribosome-independent endoribonuclease that cleaves the recognition site ‘ACA’ in single-stranded RNA\textsuperscript{12,16}. Approximately 96% of \textit{E. coli} coding sequences contain at least one MazF recognition site (Supplementary Fig. 1a). Thus, induction of MazF should inhibit cellular processes other than those protected from its action.

We characterized the impact of MazF on expression of a target gene \textit{mCherry} that contained nine recognition sites in the coding sequence (\textit{mCherry-U}) or was recorded to not contain any sites using alternative codons (\textit{mCherry-P}). MazF was introduced into an intergenic genomic site under control of an aTc-inducible promoter (P\textsubscript{TET}) in an \textit{E. coli} strain deleted for mazF (strain S2 in Supplementary Table I). The total fluorescence of mCherry-P and mCherry-U were similar in the absence of MazF, indicating that recoding the transcript did not modify expression (Fig. 1b). The MazF induction ratio is a metric used to quantify resource redistribution activity, and is defined as the ratio of total mCherry-P fluorescence in the presence to absence of MazF. Following 10 h of induction with 0 or 5 ng ml\textsuperscript{-1} aTc, the MazF induction ratio was <1 for mCherry-U and 5 for mCherry-P (Fig. 1c). The sequence protection ratio of total fluorescence, defined as the ratio of mCherry-P to mCherry-U, was ~1 or 19 in the absence or presence of MazF (Fig. 1d). Altogether, these data show that MazF significantly enhanced protected and inhibited unprotected gene expression.

To map the relationship between MazF expression and resource redistribution activity, growth and mCherry-X (X denotes U or P) expression were measured across a broad range of aTc concentrations. The total fluorescence of mCherry-U driven by an arabinose-inducible promoter (P\textsubscript{BAD}) was reduced up to 4-fold in response to aTc (Supplementary Fig. 2). In the presence of aTc, the MazF induction ratio of total fluorescence was enhanced (Fig. 1e), whereas the total biomass was lower (Supplementary Fig. 3a). The MazF induction ratio of fluorescence divided by OD600 increased with aTc and arabinose (Supplementary Fig. 3b). While the biomass normalization factor altered the quantitative value of the induction ratio, the qualitative relationship between MazF activity and protected gene expression was unmodified (Fig. 1e and Supplementary Figs 2 and 3b). These data highlight that mCherry-P expression and biomass synthesis were inversely correlated in response to MazF. In sum, our results suggest that the enhancement of the protected gene mCherry-P in MazF-induced cells is due to augmented synthesis.

To interrogate the temporal variation in expression in MazF-induced cells, cell populations were induced with mCherry-P at three time points following exposure to MazF. To account for variability in biomass across conditions, we evaluated fluorescence divided by OD600 since the qualitative relationships were not altered by the biomass normalization factor (Fig. 1b,e; Supplementary Figs 2 and 3b). To compare expression across conditions, fluorescence divided by OD600 was normalized to the maximum expression level across all conditions following 12 h of induction with 5 ng ml\textsuperscript{-1} aTc. In the absence of MazF, delayed induction by 2 h reduced mCherry-P expression by 85% (Supplementary Fig. 4a), whereas cells induced with MazF displayed a 34% decrease in mCherry-P expression (Supplementary Fig. 4b). These data indicate that heterologous expression was significantly attenuated by delayed induction in the absence of MazF, presumably by the transition from exponential to stationary phase. By contrast, delays in the induction of mCherry-P reduced expression by a smaller magnitude in the presence of MazF, indicating that MazF-induced cells preserved high-metabolic activity for a period of time.

**Results**

**Characterization of MazF for resource allocator design.**

To explore whether manipulation of resource allocation could predictably modulate circuit behaviour, we needed to develop a comprehensive reallocation mechanism that preserved core processes required for a target function, while downregulating

E. coli.
Enhancement of gluconate activity using MazF circuit. The gluconate pathway competes directly with biomass synthesis by redirecting glucose into gluconate via glucose dehydrogenase (Gdh, Fig. 2a). To determine the impact of MazF on metabolic flux, biomass and gluconate were measured as a function of time (see Methods) in cells expressing protected Gdh (gdh-P) or unprotected Gdh containing 10 MazF recognition sites (gdh-U) controlled by a P_{LAC} promoter. These experiments were conducted in a strain background that contained genetic modifications to inhibit gluconate metabolism and decouple glucose phosphorylation and transport to efficiently utilize glucose as a substrate for target metabolic pathways (strain S1 in Supplementary Table 1). As expected, cell growth was inhibited by MazF induction whereas the uninduced population continued to grow as a function of time (Fig. 2b). Cells bearing gdh-P driven by a P_{LAC} promoter displayed up to a three-fold higher gluconate concentration and five-fold higher gluconate per unit time in the presence of MazF compared to cells that were not induced with aTc (Fig. 2c; Supplementary Fig. 6a). The gluconate titre was 85% higher for cells induced with MazF compared to cells that were not induced following 18.25 h (Fig. 2d). A protected fluorescent reporter sfGFP (sfGFP-P) N-terminally fused to Gdh-U or Gdh-P increased up to 3.3 and five-fold as a function of aTc (Supplementary Fig. 6b). These data demonstrated that the MazF resource allocator could enhance metabolic flux by protecting genes in a target metabolic pathway.

Protection of host-factors to enhance resource allocation. Synthetic circuits depend on a dense network of host-genes including the transcriptional and translational machinery. Therefore, MazF-mediated decay of host factors could impact circuit functions. To investigate whether protection of support genes could improve the performance of the resource allocator, we tested whether protection of an orthogonal RNA polymerase T7 could enhance the circuit output. A protected (T7-P) or unprotected T7 RNA polymerase (T7-U containing 50 MazF...
sites) controlled by an IPTG-inducible promoter (P_{LAC}) was used to drive the expression of mCherry (Fig. 3a). The combination of T7-P and mCherry-P yielded a 21 or 7.6-fold higher expression level of mCherry compared to T7-P, mCherry-U or T7-U, mCherry-P in the presence of MazF (5 ng ml\(^{-1}\) aTc) and 1 mM IPTG. T7-P regulating an N-terminal fluorescent protein fusion of mCherry-P to Gdh-P (mCherry-P-Gdh-P) exhibited a 1.4 and 15-fold higher expression compared to T7-P, mCherry-P-Gdh-U or T7-U, mCherry-P-Gdh-P (Supplementary Fig. 7). The mCherry expression level of the T7-X, mCherry-X (Fig. 3a) and T7-X, mCherry-X-Gdh-X (Supplementary Fig. 7) circuits were differentially enhanced by protection of T7 RNA polymerase or the reporter gene (mCherry-X or mCherry-X-gdh-X) in the presence of MazF. Thus, the quantitative value of the enhancement by protection of specific genes in a circuit depended on the circuit composition.

Defining translation factors in need of protection is challenging since the basic translation machinery consists of 78 factors including ribosomal proteins and aminoacyl-tRNA synthases\(^{18}\). To identify candidates, the proteome of MazF-induced cells was measured as a function of time. The majority of the proteome (216 measured proteins) and 91% of 35 detectable ribosomal proteins varied by \(\pm 10\%\) following 5 h of induction, demonstrating that highly abundant proteins were stable for hours following exposure to MazF (Supplementary Fig. 8a). Ribosomal protein subunits S9, S20 and L17 decreased by \(\sim 20\%\) and an essential elongation factor EF-Ts decreased by approximately 80% following 5 h of induction with MazF (Supplementary Fig. 8b). In the presence of MazF, a protected version of EF-Ts (EF-Ts-P) driven by an IPTG-dependent promoter (P_{LAC}) significantly enhanced the expression of mCherry-P compared to cells that were not induced with EF-Ts-P (Fig. 3b). These results indicated that genome-wide measurements could be used to discover support genes in need of protection to augment resource redistribution activity.

Global mRNA decay could generate imbalances in the expression levels of genes in a regulatory network. For example, high concentrations of truncated mRNA fragments could saturate exonucleases that process these fragments into mononucleotides\(^{19}\). Further, mRNA cleavage generates ribosome stalling at the 3’ end of the mRNA, referred to as non-stop complexes, which require the action of ribosome recycling factors to rescue the ribosomes\(^{20}\). RNase R is a multifunctional protein that exhibits ribonuclease and ribosome recycling factor activities\(^{21}\). Co-expression of MazF and protected version of RNase R (RNase R-P) significantly enhanced the expression of mCherry-P compared to cells expressing only MazF (Fig. 3b). However, co-expression of EF-Ts-P and RNase R-P did not yield an additional enhancement in the level of mCherry-P in the presence of MazF compared to cells expressing either of the single support genes, RNase R or EF-Ts-P (Supplementary Fig. 9). These results suggested that epistasis among support genes could potentially limit incremental improvement of resource redistribution activity.

**Dissecting the role of the MazF mRNA-decay feedback loop.**

The \(\text{mazF}\) transcript is enriched for recognition sites
Figure 3 | Improvement in resource redistribution activity via protection of key support genes and evaluation of the role of the MazF mRNA-decay negative feedback loop. (a) Schematic of the orthogonal T7 RNA polymerase resource allocator circuit (top). MazF, T7 RNA polymerase (T7-X) and mCherry-X were controlled by an aTc (P_TET) and IPTG (P_LAC) and T7 (P_T7) regulated promoter, respectively. Normalized fluorescence divided by OD600 as a function of aTc for cells expressing combinations of T7-U or T7-P and mCherry-U or mCherry-P following 8.3 h of induction with 1 mM IPTG (bottom). Error bars represent 1 s.d. (n = 3). (b) Schematic of support gene (SG-P) circuit (top). The support genes included protected host factors RNase R-P and EF-Ts-P. Normalized mCherry-P OD600–1 in the presence or absence of MazF induction. The induction ratio is defined as the division of the former quantity by the latter. The sequence protection ratio is defined as the ratio of mCherry-P OD600–1 to mCherry-U OD600–1 in the presence or absence of MazF. Sequence protection ratio (middle) and MazF induction ratio (bottom) in the presence (5 ng ml−1 aTc, 125 µM IPTG) or absence (0 ng ml−1 aTc, 0 ng ml−1 IPTG) of IPTG or aTc. Cells were induced with 0.05% arabinose for 8.3 h. Error bars represent 1 s.d. (n = 4). (c) Schematic of MazF mRNA-decay feedback loop (top). MazF induction ratio of fluorescence divided by OD600 for cells expressing mazF transcripts that varied in the number of recognition sites (P37-43 in Supplementary Table I). mCherry-P was regulated by an aTc-inducible promoter (P_LAC). Cells were induced with 0 or 5 ng ml−1 aTc and 1 mM IPTG for 9.2 h. Error bars represent 1 s.d. (n = 4).

( Supplementary Fig. 1b), establishing an mRNA-decay negative feedback loop. We suspected that protection of MazF could enhance circuit performance. However, the feedback loop may modulate the regulatory dynamics of MazF and therefore influence resource redistribution activity. To investigate this possibility, we probed the role of the mRNA-decay feedback in the MazF resource allocator.

Cells (strain S3 in Supplementary Table I) bearing mazF-U on a low copy plasmid (plasmid P1 in Supplementary Table I) controlled by an aTc-inducible promoter (P_TET) and induced with 5 ng ml−1 aTc exhibited a lower steady-state mazF mRNA level compared to cells expressing mazF-P (Supplementary Fig. 10a), demonstrating that the feedback loop was actively regulating the abundance of the mazF transcript. Corroborating this result, a 35% lower threshold of aTc was required to inhibit growth in a strain expressing MazF-P compared to MazF-U (Supplementary Fig. 10b), suggesting that protection of mazF mRNA yielded a higher MazF protein level. The Hill coefficients of OD600 as a function of aTc following 11.2 h of induction were 2.6 and 5.9 for cells induced with MazF-U or MazF-P, revealing an ultrasensitive relationship between MazF activity and biomass synthesis that was significantly increased in the absence of the MazF mRNA-decay feedback loop.

Contrary to expectation, cells expressing MazF-U displayed significantly higher mCherry-P expression compared to cells expressing MazF-P across a broad range of aTc concentrations, highlighting that the negative feedback loop was a critical regulatory feature for the MazF resource allocator (Supplementary Fig. 10c). To further investigate the quantitative relationship between feedback loop strength and resource redistribution activity, we examined growth and protected reporter gene expression in cells (strain S3 in Supplementary Table I) bearing mazF sequences that varied in the number of recognition sites (Fig. 3c; Supplementary Fig. 11). The MazF induction ratio of fluorescence divided by OD600 increased with the number of sites and the wild-type mazF sequence (nine sites) generated nearly the highest output expression level (Fig. 3c). In sum, these results indicated that the activity of the mRNA-decay feedback loop was a tunable knob that could be used to modulate circuit performance.

A mechanistic computational model of cellular resource allocation was constructed to provide insight into the role of the mRNA-decay negative feedback loop on circuit behaviour (Supplementary Note). The dynamic model represented the mRNA and protein levels of key species involved in the MazF resource allocator (Supplementary Fig. 12), which compete for...
limiting ribosome pools including ribosomes (r), unprotected proteome (p), MazF (mazFp) and a protected reporter gene (FP). The growth rate (λ) function was based on a previous coarse-grained mechanistic model of gene expression and growth. A detailed description of the model and parameters are in Supplementary Note and Supplementary Tables II and III.

The relationship between the mazF’ transcription rate (mazFT) and the FP translation rate (ktransFP) is non-monotonic (Supplementary Fig. 13a), indicating that there is an optimal expression level of MazF to maximize resource redistribution activity. The model shows that the strength of the feedback loop, represented by the dissociation constant of MazF dimer (mazFpd) to the mazF’ transcript (mazFp) (KDF = koff/kdimer), is inversely correlated with the dose-response ultrasensitivity of total steady-state MazF concentration (mazFT = 2 × [mazFtp]ss + 2 × [f]ss + 2 × [p]ss + 2 × ktransFP [mazFpd]s + [mazFp]ss, where ss denotes steady-state) as a function of (Supplementary Fig. 13a). Molecular mechanisms that realize ultrasensitivity include MazF dimerization, molecular sequestration of mRNAs by ribosomes or positive feedback. In addition, thresholded control of λ by mazFT, which was observed in our experimental and modelling data (Fig. 4d; Supplementary Fig. 10b), could contribute to ultrasensitivity in the network. For high KDF corresponding to the open loop system, the model exhibits bistability manifesting as two stable steady states across a range of λ values (Supplementary Fig. 13b). Since mazF and mazFp compete for limiting ribosome pools (Supplementary Fig. 13c), bistability could arise via positive feedback established by an increase in the synthesis rate of r as a consequence of MazF-dependent mazFp decay. The MazF mRNA-decay negative feedback loop enables proportional adjustment of the mazFp concentration and reduces the potential for bistability by abolishing ultrasensitivities (Fig. 4b). As such, mazF concentration could be tuned to operate in the regime that maximized resource redistribution activity.

For a fixed value of λ, ktransFP is inversely related to KDF (Fig. 4c), qualitatively recapitulating the increase in mCherry-P with the number of binding sites in the mazF’ transcript (Fig. 3c). λ and the total concentration of the unprotected gene p decrease as a function of λ, mirroring the experimental data that showed lower OD600 and mCherry-U in the presence of aTc (Supplementary Figs 2, 3a and 10b; Fig. 4d,e). The increase in ultrasensitivity of the dose response of mazFT versus λ as a function of KDF (Fig. 4d) qualitatively reflected the enhanced ultrasensitivity of the steady-state dose response of aTc versus biomass (OD600) for cells expressing MazF-P compared to MazF-U (Supplementary Fig. 10b). The negative feedback loop strength is inversely related to the range of λ values that enhance total steady-state concentration (rT, Fig. 4f). Above a threshold value of KDF, rT decreases monotonically with λ. The mRNA-decay negative feedback has important implications for resource allocator design by enabling precise tuning of the MazF operating point by establishing a proportional relationship between λ and mazF. Indeed, this negative feedback may provide an evolutionary advantage for cells by preventing the deleterious effects of MazF overexpression that accelerated cell death (Supplementary Fig. 14).

Figure 4 | Probing the role of the MazF negative feedback loop in a dynamic computational model of resource allocation. This model demonstrates that the MazF mRNA-decay feedback loop established proportional control of MazF in the absence of MazE (λD = 0). (a) Total MazF concentration at steady state (mazF, t = 278 h) as a function of the transcription rate of mazF (mazFT) across a range of dissociation constants (KDF) in units of nM of MazF to mazF mRNA (mazFp). Here, mazF = 2 × [mazFp]ss + 2 × [f]ss + 2 × [p]ss + 2 × [f]ss + 2 × [mazFpd]s + [mazFp]ss, where ss denotes steady-state. (b) Maximum logarithmic sensitivity (ultrasensitivity) of the dose response of mazFp versus mazF across a range of KDF values. (c) Steady-state translation rate of a protected gene FP (ktransFP = ktransFP[mrez[FP]ss] as a function of KDF in the presence (λD = 2.8 nM min⁻¹) or absence (λD = 0 nM min⁻¹) of MazF. (d) Steady-state growth rate (λ) as a function of λD for different values of KDF. (e) Steady-state total unprotected proteome (rp) concentration as a function of λD for different values of KDF. (f) Steady-state total ribosome concentration (rT) as a function of λD for different values of KDF.
**MazE feedback loop impacts growth and circuit properties.** Transcriptional profiling and proteomics measurements of MazF-induced cells (strain S2 in Supplementary Table I) revealed that the mazE transcript (Supplementary Fig. 15a) and MazE protein (Supplementary Fig. 15b) were up-regulated by αtC administration. MazE is a stoichiometric inhibitor of MazF activity by sequestering MazF into an inactive complex. Stimulation of MazE synthesis in response to MazF activity establishes a molecular sequestration negative feedback loop. The protein abundance of MazF significantly exceeded MazE, explaining the lack of MazF inhibition in these conditions (Supplementary Fig. 15b). Since MazE could be used to control the activity of the MazF resource allocator, we examined the impact of MazE activity on growth and circuit properties in the model.

The transcription rate of mazE was a function of active MazF (mazFpd) in the model to capture the coupling between MazF induction and MazE synthesis (Supplementary Note). Increasing the maximum mazE transcription rate aE reduced the total active MazF concentration (total active MazF concentration was defined as \([ \text{mazF} ]_{\text{ss}} + [ \text{mazF} ]_{\text{ff}} + [ \text{mazF} ]_{\text{rf}} + [\text{mazFpd}]_{\text{ss}}, \) where ss denotes steady-state Supplementary Fig. 16a). As a result, a higher aE was required to fully inhibit cell growth in the presence of MazE (Supplementary Fig. 16b). Increasing aE shifted the regime of maximum resource redistribution activity towards higher aE values (Supplementary Fig. 16c). Ultrasensitivity in the steady-state dose response of aE versus total MazF ([mazF]ss = 2 × \([ \text{mazF} ]_{\text{ss}} + 2 × [ \text{mazF} ]_{\text{ff}} + 2 × [ \text{mazF} ]_{\text{rf}} + 2 × [\text{mazFpd}]_{\text{ss}}, \) where ss denotes steady-state Supplementary Fig. 16a) was moderately enhanced by up to ~23% in a narrow parameter regime corresponding to high Kff and intermediate aE values, presumably via molecular sequestration (Supplementary Fig. 16d). However, ultrasensitivity was significantly reduced across a broad range of aE values. The range of aE that mapped to high resource distribution activity could be adjusted by modulating both the MazE and MazF mRNA-decay feedback loops. However, in contrast to the mRNA-decay feedback, increasing the strength of the MazE feedback moderately reduced the parameter range that mapped to optimal circuit performance (Supplementary Fig. 16c). In sum, MazE is a key control parameter for the MazF resource allocator that can be used to rapidly modulate growth and resource redistribution activity.

**Transcriptional profiling of MazF-induced cells.** To evaluate the genome-wide variation in transcript abundance following MazF exposure, RNA-seq measurements of MazF-induced cells were collected every 2 min for a total of 8 min using strain S2 induced with 5 ng ml⁻¹ αtC (Supplementary Table I). The majority of the 192 endogenous protected genes increased or remained constant following induction with MazF for 8 min (Fig. 5a). A balance between synthesis and decay catalysed by RNases and MazF determines transcript abundance. Therefore, it is challenging to directly decipher the MazF-dependent transcript decay rates. Nevertheless, the number of MazF sites was negatively correlated with the mean log2 fold change of transcript abundance following 8 min of induction with αtC, indicating that on average the number of MazF sites predicted the fold change across the transcriptome (Fig. 5b, Supplementary Fig. 17).

Partitioning the transcriptome fold change dynamics into three clusters (see Methods) revealed three temporal patterns in transcript abundance in response to MazF induction: down-regulation (K1, 460 genes), pulsatile response characterized by an increase in transcript abundance at early times and decrease following a delay (K2, 148 genes) or up-regulation (K3, 331 genes, Fig. 5c). We evaluated functional or regulatory enrichments (P < 0.05 using the Fisher’s exact test) in each cluster to provide insights into the physiological impact of MazF exposure (Supplementary Table V). Cell envelope and genes regulated by Fur, MraZ and LexA were enriched in the K1 cluster (Fig. 5c; Supplementary Fig. 18). MraZ is a transcriptional repressor that controls many genes involved in cell division and cell wall biosynthesis. In addition, the cell division regulator minEF mRNA decreased significantly in the RNA-seq data (Fig. 5a), corroborating a link between MazF activity and inhibition of cell division. The K2 cluster was enriched for genes regulated by NikR, GlpR, GcvA, IHF, IscR and RsaA and amino acid and anaerobic metabolism (Supplementary Fig. 18). K2 contained numerous regulatory categories (Supplementary Table V), suggesting that the pulsatile transcript dynamics could be established by an early increase in synthesis rates and delayed down-regulation due to mRNA-decay at a threshold concentration of MazF. Genes regulated by ArgR were enriched in the up-regulated cluster K3. In addition, 11 TCA cycle enzymes were up-regulated in the RNA-seq data (P = 0.051 enrichment in K3), suggesting that MazF-induced cells exhibited high metabolic activity (Supplementary Fig. 18, Supplementary Table V). Previous work has demonstrated that fumarate production increased the frequency of persistor cells following antibiotic exposure. A closer examination of the catastrophic pathway revealed that fumarate producing enzymes were significantly induced, illustrating a connection between MazF activity and persistence via enhancement of fumarate flux.

Cold-shock genes are selectively expressed in response to cold stress and perform diverse functions including unwinding of RNA secondary structures, modulation of ribosome and DNA/RNA chaperone activity. The transcriptional profiling data revealed significant shifts in cold-shock cspBCEFG and associated rfaA, rhlB, rhlE and deaD transcript abundance as a function of time (Supplementary Fig. 20). IF-3, one of the major translation factors in *E. coli*, has been shown to mediate cold shock translational bias in response to cold stress. IF-3 increased over four-fold in the proteome data (Supplementary Fig. 8b) following 5 h of MazF induction, whereas the abundance of infC mRNA did not change significantly in response to MazF activity (Fig. 5a). Future work should interrogate the molecular mechanisms and functional connection among MazF activity, up-regulation of IF-3, and significant shifts in cold-shock transcript abundance.

As cold-shock transcripts were up-regulated in response to MazF activity, these sequences were promising candidates for engineering MazF-responsive promoters. To test the modularity of cold-shock induction by MazF, we constructed a tandem promoter composed of P_{LAC} upstream of the cspB or cspG promoter, UTR and the first 14 amino acids of CspG or CspB N-terminally fused to sfGFP-P (Supplementary Fig. 21). MazF induction increased sfGFP-P by a maximum of 20 or 80-fold, demonstrating that the cspB and cspG regulatory sequences are modular control elements that directly respond to MazF activity as an input.

**Interrogation of parameters that impact MazF activity.** A quantitative understanding of the mapping between MazF site placement and cleavage efficiency could enable tuning of the timing and degrees of protection to inform resource allocator design. Previous work demonstrated that MazF activity was inhibited by strong secondary structures and ribosomes enhanced cleavage efficiency by unwinding mRNA secondary structures during translation. To explore the dominant parameters that influence MazF cleavage efficiency, we varied the number and position of MazF recognition sites in the mCherry transcript.
genes in each category (Supplementary Table V). The median, the bottom and top edges represent the 25th and 75th percentiles and ‘*’ denote outlier data points. Dashed lines represent a two-fold threshold in transcript abundance.

Figure 5 | Time-series RNA-seq measurements of MazF-induced cells. The mean RPKM value (n = 2) was log2 transformed. (a) Scatter plot of log2 transformed RPKM measurements before induction with MazF versus induction with MazF (5 ng ml⁻¹ aTc) for 8 min. Grey and red data points denote unprotected or protected transcripts larger than 80 nucleotides, respectively. Dashed lines represent a two-fold threshold in transcript abundance. cspABCGEF and minE transcripts are highlighted. (b) Scatter plot of the number of mazF sites for each gene versus mean log2 fold change following induction with 5 ng ml⁻¹ aTc for 2 or 8 min. A 5-point moving average was applied to the data. Lines represent fitted exponential functions to the data. (c) K-means clustering of log2 fold change of 939 genes (left) that exhibited correlated dynamics between biological replicates. Box plots (right) of representative functional or regulatory enrichments in the K1 and K3 clusters according to the Fisher’s exact test (P < 0.05). On each box, the red line indicates the median, the bottom and top edges represent the 25th and 75th percentiles and ‘*’ denote outlier data points. n represents the number of genes in each category (Supplementary Table V).

To map the relationship between position and cleavage efficiency, a single MazF site was inserted at 14 positions in mCherry-P (Supplementary Fig. 22). These mCherry sequences exhibited a broad range of expression levels in response to MazF (Supplementary Fig. 22a). The output was correlated with the predicted secondary structure Gibbs free energy (ΔG) 38–47 bp upstream of the recognition site (ρ ranged between −0.7 to −0.5, P < 0.05 using the Student’s t-test) computed using NUPACK (Supplementary Fig. 22b,c). For sequences spanning upstream and downstream of the MazF site, mCherry expression was correlated (ρ = −0.6, P < 0.05 using the Student’s t-test) with ΔG (39–40 bp, Supplementary Fig. 22d). However, the ΔG of the sequence downstream of the recognition site was not correlated with the expression level of mCherry across a broad range of window sizes (Supplementary Fig. 22e). Therefore, MazF cleavage efficiency could be predicted using the folding energy of the local mRNA secondary structure upstream or across the recognition site.

To provide insight into the programmability of MazF cleavage efficiency, we interrogated whether measurements of mCherry variants containing a single MazF site (Supplementary Fig. 22a) could predict the expression of mCherry sequences containing combinations of sites. mCherry expression decreased as a function of the number of recognition sites in the presence of MazF (Supplementary Fig. 22f). The product of the single site mCherry expression levels could predict the expression of the multi-site variants (P < 4e−6 using the Student’s t-test), suggesting that combinations of MazF recognition sites could be used to modulate the degree of transcript protection.

Discussion

A major goal of synthetic biology and metabolic engineering is to develop strategies to control the resource economy of cells for switching between modes of growth and production. During a production phase, cellular energy and resources are focused on specific pathways, while minimizing resource expenditure towards nonessential cellular operations. Towards these objectives, previous work leveraged tunable enzymatic degradation of a metabolic hub that determines the direction of metabolic flux to augment the yield and titre of a metabolic pathway two-fold. While this strategy provided localized control of metabolic flux, it does not modulate the global allocation of subsystems such as transcription and translation. On a larger scale, inducible regulation of RNA polymerase subunits was recently used to control E. coli growth. However, this mechanism cannot be generally applied to redirect resources towards engineered networks.
Here, we showed that synthetic circuits could exploit shifts in cellular physiological state due to MazF activity, suggesting that intracellular resources could be diverted via programmable mRNA decay. This approach could be harnessed for diverse applications by protecting genes in an engineered network and systematically discovering key support factors beyond the engineered pathway in need of protection. Recent advancements in DNA synthesis technologies will facilitate large-scale recoding of support genes to protect from MazF activity. A utility of this approach is to enhance target functions that compete directly with biomass synthesis, such as exploiting microbes as ‘cell factories’ to synthesize chemicals or biomolecules of interest. Further, MazF activity could potentially minimize unintended environmental impact due to cell proliferation, while allowing engineered cells to carry out a desired function in a complex environment. Coupling this strategy to dynamic regulation of MazE would enable periodic resuscitation of cellular sub-systems and maintain metabolic activity over longer time scales.

MazF regulates orders of magnitude more genes simultaneously compared to other technologies such as CRISPR5,46. Homologues of MazF that recognize 3, 5 and 7-bp recognition sites have been identified in diverse bacterial species47–49. Active site mutations have been shown to modify the MazF sequence specificity, suggesting that protein engineering could be used to expand the diversity of MazF recognition site sequences50. The variation in recognition sequence specificity could be used to tune the number of genes targeted by MazF.

In addition to the unknown myriad effects of MazF-induction on network activities, there are several limitations to optimizing the MazF resource allocator. MazF activity increased the abundance of a set of host-cell transcripts (cluster K3 in Fig. 5c), which sequesters resources away from engineered pathways. In addition, MazF activity has been shown to yield a heterogeneous ribosome pool, limiting the time scale required to shift metabolic flux. To rapidly manipulate metabolic flux, induction of MazF could be coupled with proteases8 for targeted control of protein abundance. As the protease decays, stoichiometric relationships required for protein activity must be maintained31. Further, MazF has been shown to establish a futile cycle of continuous RNA synthesis and decay, resulting in energy dissipation56. To minimize an energy deficit, orthogonal T7-P could be used to drive the engineered pathway, while at the same time inactivating native RNA polymerases.

Cells have evolved numerous feedback mechanisms to optimize ribosome concentrations to match changes in environmental conditions, including nutrient quality and abundance53,54. These growth-rate dependent couplings to cellular processes including transcription, translation and replication can influence the behaviour of synthetic circuits. In MazF-induced cells, the consequences of growth rate inhibition on cellular sub-systems remain unresolved. The stringent response is not activated in MazF-induced cells, which allows cells to maintain ribosome synthesis and cellular maintenance55. A detailed understanding of network activities and resource partitioning in MazF-induced cells will allow for exploitation of this unique physiological state for diverse biotechnological applications.

Top-down approaches such as MazF could be used to discover host factors that preserve high metabolic activity in the absence of growth. Genome engineering could be used to protect these pathways from MazF activity56. Optimal regulatory strategies should be designed to balance enhancement of resource redistribution activity and degradation of cellular support subsystems over long time scales. For example, MazF could be transiently induced until energy degrades to a threshold that triggers rapid inhibition of MazF activity via MazE and allows rebalancing of the proteome57. Altogether, advances in regulatory control strategies and large-scale recoding may enable the design of protected and unprotected orthogonal sub-genomes that dynamically switch between cellular operations.

Methods

Cloning and strain construction. MazF was deleted from the E. coli BW25113 using lambda-red recombination and confirmed by colony PCR. MazF was introduced into an intergenic region referred to as SafeSite 1 (chromosomal position 34715) under control of an α-tic-inducible promoter (Ptic). PCR amplifications were performed using Phusion High-Fidelity DNA Polymerase (NEB) and oligonucleotides for cloning and strain construction were obtained from Integrated DNA Technologies. Standard cloning methods were used to construct plasmids. Plasmids were derived from previously generated construct library58. A list of plasmids and strains used in this study can be found in Supplementary Table I.

Growth conditions and plate reader experiments. For plate reader experiments, cells were grown at 37 °C for ~6–8 h, and then diluted to OD600 of 0.01 in a 96-well plate (Corning) in LB Lennox media (Sigma). In 96-well plates, cells were grown in 200 μl volumes at 37 °C covered by a gas-permeable seal (Fisher Scientific) in a M1000 (Tecan) or Synergy 2 (BioTek) plate reader. Cells were cultured for 1–2 h in the plate reader before inducer administration. The method measured cell density (OD600) and fluorescence every 10 min for 15 h. The M1000 excitation and emission wavelengths were 485, 510 nm for GFP and 587, 610 nm for RFP (5 nm bandwidth). The BioTek excitation and emission wavelengths were 485, 528 nm for GFP and 560, 620 for RFP (20 nm bandwidth). The M1000 and Synergy 2 measured absorbance at 600 nm (OD600) to quantify total biomass. For each experiment, the minimum value of fluorescence or OD600 across all conditions was subtracted from fluorescence or OD600 measurements. Normalized fluorescence was computed by dividing by the maximum value across conditions. Normalized fluorescence divided by total biomass (OD600) was computed by dividing total fluorescence by OD600 and then normalizing to the maximum value across conditions. For plate reader experiments, biological replicates consisted of cells inoculated into different wells in a 96-well plate that were exposed to equivalent inducer concentrations.

qPCR measurements. Oligonucleotides for quantitative real-time PCR (sequences are listed in Supplementary Table IV) were designed using Integrated DNA Technologies. Total RNA of 500 ng was reverse transcribed using the iScript complementary DNA (cDNA) synthesis kit (Bio-Rad). The reaction mix contained 5 μl of SsoAdvanced Universal Probes Supermix (Bio-Rad), 0.5 μl primer and probe corresponding to 250 nM primers and 125 nM probe (20× stock) and 0.5 μl of cDNA. qPCR measurements were performed using a CFX96 real-time PCR machine (Bio-Rad). The relative expression levels were determined by a 2^−ΔΔCt method. Each sample was normalized by the cycle threshold geometric mean using reference genes rpsK and cysG59. Biological replicates consisted of three E. coli cultures exposed to equivalent inducer concentrations (0 or 5 ng ml−1). Three qPCR technical replicates were performed and averaged for each sample.

Glucionate measurements. KTS0221G mazF::α (strain S1 in Supplementary Table I) strains bearing pBbA6c-gdh-X (plasmid P8-9 in Supplementary Table I) and pBbS2k-mazF-U (plasmid P1) were grown in LB medium at 37 °C overnight and used to inoculate a 10 ml culture the next morning at an OD600 of 0.05. At OD600 of 0.3, 1.5% glucose, 1 mM IPTG and 5 or 0 ng ml−1 were administered to growth cultures. Diluted samples were collected at the specified time and centrifuged at 5000 g for 5 min to isolate the supernatant. The supernatant samples were analysed for glucolic acid using a 1,200 Series liquid chromatography system (Agilent Technologies) coupled to an LTQ-XL ion trap mass spectrometer (Thermo Scientific) equipped with an electrospray ionization source. Aliquots of the diluted samples were injected onto a Rezex ROTA-Organic Acid H + (8%) (150 mm × 4.6 mm) column (Phenomenex) equipped with a Carbo-H (4 × 3 mm2) guard column (Phenomenex). Glucolic acid was eluted at 55 °C at ~3.5 min with an isocratic flow rate of 0.3 ml min−1 of 0.5% (v/v) formic acid in water. Precursor ion m/z 139.1 was selected in negative ion mode using an isolation window of m/z 2 and was fragmented with a normalized collision energy of 35. Fragment ions were analysed in the range of m/z 50–200. m/z 128.5–129.5 was selected as pseudo-MRM transition for compound quantification. Resulting peak areas were compared to an external standard calibration in the range of 0.2–200 μM. The source parameters were ion spray voltage: 4 kV; capillary temperature: 500 °C; capillary voltage: 20 kV; sheath gas flow: 2; auxiliary gas flow: 5; and sweep gas flow: 10 (all arbitrary units). Technical replicates were performed by measuring the sample three independent times.
The experiment was repeated three independent times. These experiments showed that the MazF-induced cells expressing Gdh-P yielded the highest gluconate concentrations compared to uninduced cells and MazF-induced cells expressing Gdh-U.

**Proteomics.** BW25113 maxF:A, SafeSite::tetR~P_TET~mazF (strain S2 in Supplementary Table I) was grown overnight in LB at 37 °C and then diluted to an OD600 of 0.05 in a 500 ml LB culture. At OD600 of 0.5, cell populations were induced with 5 ng ml~1~ 1 Tc and 40 ml of the cultures were collected separately every hour and centrifuged for 5 min at 4,300 g. Proteomic samples were prepared for analysis by lysing the cell pellets and extracting the proteins using the chloroform/methanol precipitation method. The proteins were resuspended in 100 mM AMBIC with 20% methanol and reduced with tris(2-carboxyethyl) phosphine for 30 min, followed by addition of iodoacetamide (IAA; final conc. 10 mM) for 30 min in the dark, and then digested overnight with MS-grade trypsin (1:50 w/w trypsin:proteins) at 37 °C. Peptides were diluted at ~20 °C until analysis.

Samples were analysed on an Agilent 1290 UHPLC–6550 QTOF liquid chromatography mass spectrometer (LC–MS/MS; Agilent Technologies) system and the operating parameters for the LC–MS/MS system were described previously. The replicates were separated on a Sigma-Aldrich Ascentis Express Peptide CS-E C18 column (2.1 x 100 mm, 2.7 mm particle size, operated at 60 °C) and a flow rate of 0.4 ml min~1.~ The chromatography gradient conditions were as follows: from the initial starting condition (98% buffer A containing 100% water, 0.1% formic acid and 2% buffer B composed of 100% acetonitrile, 0.1% formic acid) the buffer B was increased to 10% of the final condition (buffer B was increased to 40% over 117 min, then increased to 90% B over 3 min and held for 8 min, followed by a ramp back down to 2% B over 1 min, where it was held for 6 min to re-equilibrate the column to the original conditions. The data were analysed with the Mascot search engine version 2.3.02 (Matrix Science) and filtered and validated using Scaffold v4.3.0 (Proteome Software Inc.) Replicates consisted of four aliquots of an *E. coli* culture exposed to 5 ng ml~1~ 1 Tc for different lengths of time. Shotgun proteomics was performed independently on each sample.

**RNA-seq library construction and sequencing.** BW25113 maxF:A, SafeSite::tetR~P_TET~mazF (strain S2 in Supplementary Table I) was grown overnight in LB at 37 °C and then diluted to an OD600 of 0.05 in a 10 ml LB culture. At an OD600 of 0.5, cell populations were induced with 5 ng ml~1~ 1 Tc and 40 ml of the cultures were collected separately as follows: 200 μl of the cell cultures were added to 400 μl of RNAprotect (Qiagen) to stabilize the RNA, incubated for 5 min at room temperature and then spun down for 10 min at 5,000g. Total RNA was isolated using RNeasy purification kit and treated with DNase I (Qiagen). The Functional Genomics Lab (FGL), a QB3-Berkeley Gene Research Facility at UC Berkeley, constructed the sequencing libraries. At the FGL, Ribo-Zero RNA Removal Kits (Illumina) were used to remove ribosomal RNA and ERCC RNA Spike-In Control Mixes (Ambion by Life Technologies) were added to the samples. The library preparation was performed on an Apollo 324 with PrepX RNAseq Library Prep Kits (WaferGen Biosystems, Fremont, CA), and 18 cycles of PCR amplification was used for index addition and library fragment enrichment. Biological replicates consisting of two *E. coli* culture aliquots exposed to 5 ng ml~1~ 1 Tc were collected at the specified times. RNA-seq libraries were constructed independently from each sample.

**RNA-seq data analysis.** The read counts were mapped onto the MG1655 genome using Bowtie 1 (ref. 61) on the galaxy webserver~62.~ Reads per kilobase of transcript per million (RPKM) was computed by multiplying the number of mapped reads by 10~10~ and then dividing by the gene length and median number of total reads for each condition. For clustering analysis, the correlation coefficient (ρ = 0.9) between two biological replicates as a function of time was used as a threshold to remove genes that exhibited variability between replicates. The log~2~ fold change was partitioned into clusters using the K-means algorithm (MATLAB). To determine an optimal number of clusters, the sum of squared errors was computed for each data point from the corresponding cluster centroid across a range of K-values (1–10). The Elbow method was used as a heuristic to select the optimal number of partitions that minimizes the sum of squared errors. The Fisher’s exact test (P < 0.05) was used to evaluate enrichment of genes based on TIGRFAM annotations (MicrobesOnline) or transcription factor network (RegulonDB). Supplementary Table V contains a list of genes in the enriched categories.

**Computational modelling.** We used custom code for computational modelling and data analysis in MATLAB (Mathworks) and Python. Details about the model construction are provided in Supplementary Note. Model species and parameters are described in Supplementary Tables II and III. Supplementary Software contains MATLAB code for the MaxF resource allocation model.

**Characterization of cell viability.** A BW25113 maxF:A strain (strain S3 in Supplementary Table I) transformed with pBB8sk-mazF-U or pBB8sk-mazF-P (plasmid P1-2 in Supplementary Table I) was grown overnight at 37 °C in LB media and then diluted to an OD600 of 0.01 in 5 ml LB media. At an OD600 of 0.3, 5 ng ml~1~ 1 Tc dissolved in 100% ethanol was used to induce the cells and an equivalent volume of 100% ethanol was administered to the uninduced cell populations. Following 0 and 7 h, cells were prepared for fluorescent microscopy using the LIVE/DEAD BacLight Bacteria Viability Kit (Thermo Fisher) to characterize the fraction of viable cells across the population. Microscope images were collected using a Zeiss Axios Observer D1 and Plan-Apochromat 63/1.4 Oil Ph3 M22 objective (Zeiss). Cells were imaged using excitation BP 470/40 and emission BP 525/50 (Filter Set 38 High Efficiency) or excitation 560/40 and emission BP 630/75 (Filter Set 45). Images were captured with a Hamamatsu ORCA-Flash4.0 using the ZEN Software (Zeiss). Cell Counter (Fiji)~63~ was used to analyse the images and quantify the number of viable and dead cells. Technical replicates consisted of aliquots of *E. coli* cultures that were independently prepared for microscopy using the LIVE/DEAD protocol.

**Statistics.** Statistical analyses and sample size for each experiment are described in the figure legends and Methods subsections. Data represent the mean ± 1 s.d., unless noted otherwise. P < 0.05 was considered significant.

**Code availability.** The authors declare that all computer code supporting the findings of this study is available on request.

**Data availability.** The RNA-seq data in this study have been deposited in the National Center for Biotechnology Information (NCBI) Gene Expression Omnibus (GEO) with accession code GSE94998. All other data supporting the findings of this study are available on request.

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