## Supplementary Information for:

## **Massively parallel characterization of engineered transcript isoforms using direct RNA sequencing**

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# **Supplementary Notes Page** Supplementary Note 1: Library coverage calculation  $\qquad \qquad \qquad 2$ Supplementary Note 2: Transcription profile features 3 Supplementary Note 3: Modelling direct RNA sequencing examplementary Note 3: 6

### **Supplementary Figures**



## **Supplementary References** 27

1

#### **Supplementary Note 1: Library coverage calculation.**

We estimated library coverage using the approach presented by Patrick *et al*. <sup>4</sup> to calculate the expected number of distinct sequences in a library chosen at random from a set of sequence variants. Given a pooled library containing *L* sequences, and a set of *V* equiprobable variants, let  $v_i$  be one of the possible variants. Since the variants are equiprobable, the mean number of occurrences of *vi* in *L* is

$$
\lambda = L / V. \tag{S1}
$$

For  $\lambda \ll L$  (i.e.,  $V \gg 1$ ), the actual number of occurrences of  $v_i$  in L is essentially independent of the number of occurrences of any other variant  $v_i$  where  $j \neq i$ , and therefore well-approximated by

a Poisson distribution

$$
P(x) = \frac{e^{-\lambda} \lambda^x}{x!},
$$
\n(S2)

where *P(x)* gives the probability that *vi* occurs exactly *x* times in the library. The probability that *vi* occurs at least once is given by  $1 - P(0) = 1 - e^{-\lambda} = 1 - e^{-L/V}$ . Therefore, the number of distinct variants expected in the library is given by

$$
C \approx V(1 - e^{-L/V}),\tag{S3}
$$

and the fractional completeness of the library is

$$
F = \frac{c}{v} \approx 1 - e^{-L/V}.\tag{S4}
$$

The library size required for fractional completeness *F* is therefore

$$
L \approx -V\ln(1 - F). \tag{S5}
$$

In our case, *V* = 1183 variants and we require a fractional completeness of  $F > 1 - \frac{1}{1183} = 0.99915$ to ensure with high probability the representation of all variants in the library. This necessitates a library size of at least  $L \approx -V\ln(1 - 0.99915) = 8364$ . To achieve this, we performed a transformation protocol that used 10 large trays with approximately 50,000 transformants per tray (**Methods**), resulting in  $L \approx 500000$ .

#### **Supplementary Note 2: Transcriptional profile features**

After characterization of our initial transcriptional valve library, there were several key features that were present within the generated transcriptional profiles. First, we noticed that dRNA-seq reads often had 6 nt of their 5' sequence truncated (**Supplementary Figure 6a**), which could make it difficult to determine precise transcription start sites. As dRNA-seq progresses from the 3' to 5' end of an RNA molecule, this short region likely corresponds to the point where the motor protein that ratchets the RNA molecule through the pore reaches the 5'-end and releases the molecule, causing an increased error rate or removal of the short sequence still contained within the pore.

Second, we found that all dRNA-seq read depth profiles showed drops in read depth when moving from the 3'- to 5'-end (**Supplementary Figure 6**). Such a feature is found in all nanopore dRNA-seq studies to date covering RNA samples from many different organisms<sup>1,2</sup>. It is thought to arise due to fragmentation of full-length RNA molecules (e.g., by shearing caused during pipetting) and/or premature abortion during sequencing resulting in truncated reads. In contrast, only small drops were observed for nanopore DNA sequencing of the constructs (**Supplementary Figure 6a**), possibly due to the greater stability of the molecule <sup>3</sup>.

The small proportion of sequencing reads representing RNA fragmented within the barcodes used for mapping leads to a minority of erroneous read mappings. This occurs where the sequencing read matches only part of the barcode and it is impossible to accurately align that read to a particular combinatorial design. We removed sequencing reads arising from these mapping artefacts by selecting only reads with alignment across the spacer, modifier and the first 20 nt of the terminator. The model we outline later corrects for the removal of these reads. While this means that any drops within this region would be missed, studying the profiles generated without omitting these reads did not reveal any noticeable drops in this region. Termination of T7 RNAP requires both a hairpin structure and U-tract and while both of these elements are found in different modifiers, neither of them are found together, making drops caused by termination highly unlikely. Nonetheless, this presents a limitation for studying combinatorial libraries using this method – only transcriptional drops at the end of the barcode can be studied.

To validate the hypothesized causes of RNA fragmentation and explore their possible impact on *Te* measurements, we developed a mathematical model (**Supplementary Note 3**) and used data from an RNA Control Strand (RNA CS) that is externally 'spiked-in' to each dRNA-seq experiment for quality control assessments. Because the RNA CS is a single fixed length sequence, we could use it to test how different amounts of fragmentation or sequencing abortion affect the shape of the read depth profile recovered. We found that experimental data could be well described by a simple model with three probabilistic processes: fragmentation before ligation of sequencing adapters, successful adaptor ligation, and sequencing read truncation (**Supplementary Note 3**; **Supplementary Figure 3**). Sequencing read truncation could be caused by RNA fragmentation (after adapter ligation) and/or early abortion of the sequencing process. We found that the impact of these effects on *Te* was small (**Supplementary Figure 4**).

RNA fragmentation meant that many sequencing reads did not contain an intrinsic barcode. To demultiplex sequencing reads using our pipeline, reads are assigned via best alignment to an intrinsic barcode. Therefore, any reads not containing an intrinsic barcode cannot be mapped to a design. Fragmentation causes a significant reduction in the number of reads mapping to an intrinsic barcode (only ~20% of the total reads had an alignment to a barcode). Therefore, improvements in experimental protocols to reduce fragmentation/truncation or the incorporation of methods to enrich barcode containing reads (e.g., using 'read until' technologies <sup>42</sup> or sequence-specific dRNA-seq) could both improve the accuracy of  $T_e$  calculations and increase the size of the libraries that can be assessed using a single sequencing run.

While read profiles for RNA CS decrease only towards the 5'-end, profiles for designs decrease in both directions away from the barcode. It is not clear why this is the case since the RNA CS sequence was included in the *in vitro* transcription reaction and therefore was exposed to the same experimental conditions as our designs. It could reflect increased degradation of *in vitro* transcribed RNA, or a gradual drop-off of T7 RNA polymerase during the process of transcription, both of which would not affect the measured termination efficiencies.

A third observation was that in the case of poor polyadenylation, significant drops in read depth were seen outside of the core terminators and predominantly at short poly-A sequences >3 nt in length (**Supplementary Figure 6**). When preparing RNA for dRNA-seq a poly-A tail is required for ligation of sequencing adapters to the 3'-end of the RNA molecules. As *in vitro* transcription of our constructs will not produce transcripts of this form, we used *E. coli* poly(A) polymerase to polyadenylate all the RNAs produced (**Methods**). Analysis of the dRNA-seq data showed <10 nt poly-A tails were present, which were shorter than other dRNA-seq runs we had previously performed (**Supplementary Figure 5**).

We hypothesized that inefficient polyadenylation allows for fragmented RNAs with a short poly-A end to become enriched during sequencing and thus causes notable drops at these points within a construct that do not correspond to termination events. Our subsequent dRNA-seq runs with efficient polyadenylation do not show these drops in read depth at adenosine homopolymer regions. For runs with inefficient polyadenylation (not characterized in this paper), we could partially correct read profiles for designs containing parts with poly-A regions in their template

4

strand (i.e., I10, T13 and T27) by retaining only mapped reads which do not terminate at a poly-A motif outside the terminator hairpin (**Supplementary Figure 6c**). However, even with this correction, *Te* measurements were significantly affected for all designs (**Supplementary Figure 6d**) and therefore we repeated these experiments with efficient polyadenylation.

#### **Supplementary Note 3: Modelling direct RNA sequencing**

We developed a simple probabilistic model to capture the key processes impacting the reads recovered from a direct RNA sequencing (dRNA-seq) run. The following figure provides an overview of the major steps.



**Overview of the direct RNA sequencing model.** Reads are denoted by squiggles that are color coded to show core regions (e.g., blue region is the intrinsic barcode). Red dots show points of random fragmentation, orange oblongs represent sequencing adapters attached to only the 3'-end of an RNA molecule, and green ticks denote reads that contain a complete barcode sequenced and which are used to generate a read depth profile. *Pf*, *Pa*, and *Pt* are probabilities that reads are selected for each of the modification steps (i.e., random fragmentation, adapter ligation, and truncation, respectively).

We begin by assuming that all starting RNA transcripts correspond to either an isoform that terminates at the transcriptional valve or at an appropriate point downstream of the valve. First, reads are chosen with probability *Pf* to become fragmented at a random location along their length. This step captures the inevitable fragmentation that occurs when extracting and purifying an RNA sample. Next, sequencing adapters are attached to full length transcripts and fragmented RNAs with probability *Pa* and only molecules with an adapter attached are taken forward for sequencing. Sequenced molecules are then chosen with probability *Pt* for truncation at a random position along the sequence. This step captures possible further fragmentation of the RNA during sequencing library preparation whereby only the fragment containing the adapter is sequenced, or possible truncation of reads due to premature termination during the sequencing of a molecule. In both cases, this significantly reduces the information captured per read and renders many reads impossible to demultiplex when truncation occurs downstream of the intrinsic barcode. Finally, we filter out any that do not contain a complete transcriptional valve design (i.e., intrinsic barcode). Reads without a full barcode cannot be uniquely identified and so the reads are removed during the demultiplexing step. Reads that make it through these steps are then used to generate a read depth profile.

To demonstrate the model's ability to capture read depth profiles generated from real sequencing data, we made use of the RNA Control Strand (CS) that is externally 'spiked-in' to all dRNA-seq runs for Quality Control (QC) purposes. The RNA CS is a single known sequence unlike any other in our library and only consists of full-length RNA molecules. Fitting our model to dRNA-seq data from the two biological replicates, we found that parameter values of  $P_f$  = 0.1,  $P_a$ = 0.66 to 0.90 (depending upon the sequencing run) and  $P_t$  = 0.45 enabled a close fit for all sequencing runs, with only minor deviations at 5' and 3' ends of the RNA CS sequence (**Supplementary Figure 3a**). We also assumed the presence of an intrinsic barcode in the center of the RNA CS sequence and found that our model could also accurately predict read depth profiles recovered after demultiplexing of the real dRNA-seq data (**Supplementary Figure 3b**). This suggests that the read distribution that is generated by the model closely fits that recovered from sequencing.

Finally, to assess how well the observed read depth profiles matched the ground truth, we used the model with parameters fitting to the real dRNA-seq data for RNA CS to simulate the sequencing process on synthetically generated transcripts for a hypothetical set of transcriptional valves with termination efficiencies varying between 0 and 1. By comparing the actual termination efficiency of each hypothetical valve with the observed termination efficiency measured from the generated read depth profiles, we found a slight over estimation in *Te* (**Supplementary Figure 4**). To ensure this didn't bias our measurements for the data from the real transcriptional valves, this deviation was corrected for by subtracting the calculated error from the observed termination efficiency seen in the model simulations, to give a final  $T_e$  value. Though  $P_t$  varied between sequencing runs, the error correction for any given *Te* value was found to be consistent across sequencing runs (±1% deviation).



**Supplementary Figure 1: Analysis of library assembly.** (**a**) Number of DNA-seq reads for each design, ordered by number of reads. (**b**) Number of dRNA-seq reads for each design, ordered by number of reads. (**c**) Frequency of each part in the DNA-seq (left) and dRNA-seq (right) data. Part and design frequencies were calculated relative to the total number of annotated sequencing reads. (**d**) Number of single nucleotide polymorphisms (SNP) per design.



**Supplementary Figure 2: Design of library used to optimize demultiplexing.** (**a**) The library consists of 5 spacers (S1–S5), 18 modifiers (all parts with references beginning with M1–M3) and 6 terminators (T2–T7), resulting in 540 unique designs. For part sequences see **Supplementary Table 1**. (**b**) Modifiers were based upon 3 random starting template sequences, represented by different colored subsequences. From each template sequence 6 variants were made, each containing different proportions of the template sequence indicated by the number of base pairs: 11 bp sub-sequence, 20 bp sub-sequence, full 30 bp sequence, a 20 bp sub-sequence with Utract interactor motif, a 20 bp sub-sequence with A-tract interactor motif, a 20 bp sub-sequence with structural motif.



**Supplementary Figure 3: Fitting model to direct RNA sequencing data.** (**a**) Read depth profiles shown for all reads mapping to the RNA CS sequence for two dRNA-seq biological replicates (filled red) and fitted dRNA-seq model used to simulate the processing of the total number of reads with a BLASTN alignment to the RNA CS sequence, where  $P_f$  = 0.1,  $P_a$  = 0.8,  $P_t$ = 0.45 (dashed black line for observed profile, solid black line for the model ground truth). (**b**) Read depth profiles for reads that map to the grey 'intrinsic barcode' for the real dRNA-seq data (filled red) and fitted model (dashed black line for observed profile, solid black line for the model ground truth). The termination efficiency for the RNA CS 'intrinsic barcode' is zero.



**Supplementary Figure 4: Deviation between observed and actual termination efficiencies.**  Each point denotes a model simulation based on 100,000 simulated reads for transcriptional valves with varying termination efficiencies and parameter values of  $P_f$  = 0.1,  $P_a$  = 0.87 and  $P_t$  = 0.45 (**Supplementary Note 2**). Dashed line shows *y* = *x*.



**Supplementary Figure 5: Polyadenylation efficiencies.** Histograms showing the varying lengths of RNA poly-A tail lengths for several sequencing libraries prepared in this work (**Supplementary Table 2**). RNA from L3 and L4 were pooled and prepared together as a single sequencing library.



**Supplementary Figure 6: Impact of polyadenylation efficiency on direct RNA sequencing read profiles.** (**a**) Normalized sequencing read depth profiles from nanopore-based DNA-seq and dRNA-seq for 42 designs containing the same core terminator T33 (non-terminating control) and modifiers of length 30 nucleotides. Vertical dotted lines denote transcript and valve boundaries. Plasmid map illustrated beneath, to scale. Grey shaded region is expanded in the panel below. (**b**) Expanded region from panel A showing dRNA-seq read depth profiles with dots corresponding to adenosine nucleotides. Adenosine homopolymers >3 nt in length are highlighted in red and their lengths are shown below. (**c**) Corrected (dashed grey lines) and raw (solid black lines) dRNAseq read depth profiles for two different designs where the core terminator contains an adenosine homopolymer within the terminator sequence. Vertical dotted lines indicate spacer-modifier and modifier-terminator boundaries. (**d**) Comparison of estimated termination efficiency of designs from library L2 with and without efficient polyadenylation during sequencing library preparation.



**Supplementary Figure 7: Comparison of termination efficiencies across experimental replicates.** (**a**) Comparison of termination efficiency between experimental replicates of the same library (L2). (**b**) Comparison of termination efficiency of constructs shared between two different libraries (L2 and L3). Each point represents a single transcriptional valve design and dotted line shows the linear regression.  $R^2$  is the square of the Pearson correlation coefficient. See **Supplementary Table 2** for library compositions.



**Supplementary Figure 8: Analysis of possible predictors of termination efficiency.** (**a**) Scatter plot for each terminator showing  $T_e$  against percentage GC content of each design. Calculation based on 80 nt upstream of 3'-end of design. (**b**) Scatter plot for each terminator showing *Te* against the thermodynamic minimum free energy of each design. Calculation using default settings, based on 120 nt upstream of 3'-end of the design. (**c**) Scatter plot for each valve showing *Te* against the thermodynamic minimum free energy of each valve sequence. All folding energies calculated using RNAfold<sup>5</sup>.



**Supplementary Figure 9: Effect of U-tract changes on termination efficiency.** Scatter plot showing how the absolute change in termination efficiency increases with an increasing number of U's in the U-tract. Each point corresponds to an individual terminator.

## **Supplementary Table 1: Oligonucleotide sequences**























\* T75 also referred to as T99U

#### **Supplementary References**

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