# Swayam: Distributed Autoscaling to Meet SLAs of Machine Learning Inference Services with Resource Efficiency 

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## APPENDIX

Assumption 1. The average time to send a message from any frontend to any backend is $d_{1}$ and the average time to send a message from any backend to any frontend is $d_{2}$. Requests arrive at an average rate of $\lambda$ and that the average time to service a request is $1 / \mu$.

DEFINITION 1. RAND LB Policy: Upon receipt of a request from the broker, the frontend immediately forwards it to a random backend. If the backend is busy, it sends back a busy response to the frontend. Upon receipt of a busy response, the frontend forwards the request to another random backend after $\Delta$ time units.

Theorem 1 (Waiting Time Distribution). If there are $n$ back ends, and requests are assigned to backends as per the RAND LB Policy, then the expected $p^{\text {th }}$ percentile waiting time of the requests can be approximated as:

$$
\begin{equation*}
\omega_{p}=d_{1}+\left(\frac{\ln \left(1-\frac{p}{100}\right)}{\ln \left(\frac{\lambda}{n \cdot \mu}\right)}-1\right) \cdot\left(d_{1}+d_{2}+\Delta\right) \tag{1}
\end{equation*}
$$

Proof. Assume that $d_{1}, d_{2}, \Delta \ll 1 / \mu$. As a result, the duration for which the system remains non-work-conserving is negligible Thus, the probability that any backend is busy at any given point of time is given by the overall system utilization:

$$
\begin{equation*}
P_{b u s y}=\frac{\lambda}{n \cdot \mu} . \tag{2}
\end{equation*}
$$

Similarly, let the probability that any backend is idle at any given point of time be denoted as

$$
\begin{equation*}
P_{i d l e}=1-P_{b u s y}=1-\frac{\lambda}{n \cdot \mu} . \tag{3}
\end{equation*}
$$

Let $P_{r}$ denote the probability that a request finds an idle backend after $r$ retries, i.e., $P_{r}$ denotes the probability that a request is assigned to busy backends during the first $r$ attempts, and only in the $r+1^{s t}$ retry, the request is assigned to an idle backend. Thus,

$$
\begin{equation*}
P_{r}=\left(P_{\text {busy }}\right)^{r} \cdot P_{i d l e} \tag{4}
\end{equation*}
$$

Let $W_{r}$ denote the waiting time of the request that finds an idle backend after $r$ retries. $W_{r}$ consists of $r$ round-trip latencies for the first $r$ attempts, $r$ delays of time $\Delta$ each enforced by the frontend, and a single frontend-to-backend communication latency for the last successful attempt. Thus,

$$
\begin{align*}
W_{r} & =r \cdot\left(d_{1}+d_{2}\right)+r \cdot \Delta+d_{1} \\
& =r \cdot\left(d_{1}+d_{2}+\Delta\right)+d_{1} \tag{5}
\end{align*}
$$

Let $\omega_{p}$ denote the $p^{t h}$ percentile waiting time and suppose that it consists of delays due to $r_{\max }$ retries. Thus, $\omega_{p}=W_{r_{\max }}$, i.e.,

$$
\begin{align*}
& \omega_{p}=r_{\max } \cdot\left(d_{1}+d_{2}+\Delta\right)+d_{1} \\
\equiv & r_{\max }=\frac{\omega_{p}-d_{1}}{d_{1}+d_{2}+\Delta} . \tag{6}
\end{align*}
$$

If any request requires less than or equal to $r_{\max }$ retries to find an idle backend, then its waiting time is also less than or equal to $\omega_{p}$. Therefore:

$$
\begin{aligned}
& \sum_{k=0}^{r_{\max }} P_{k}=\frac{p}{100} . \\
\equiv & \sum_{k=0}^{r_{\max }}\left(\left(P_{\text {busy }}\right)^{k} \cdot P_{\text {idle }}\right)=\frac{p}{100} . \\
\equiv & P_{\text {idle }} \cdot \sum_{k=0}^{r_{\max }}\left(P_{b u s y}\right)^{k}=\frac{p}{100} .
\end{aligned}
$$

\{by using sum of geometric progression\}

$$
\equiv P_{i d l e} \cdot \frac{1-\left(P_{b u s y}\right)^{r_{\max }+1}}{1-P_{b u s y}}=\frac{p}{100} .
$$

\{from Eq. 3 \}

$$
\equiv 1-\left(P_{b u s y}\right)^{r_{\max }+1}=\frac{p}{100}
$$

\{from Eq. 2 \}

$$
\begin{aligned}
& \equiv 1-\left(\frac{\lambda}{n \cdot \mu}\right)^{r_{\max }+1}=\frac{p}{100} \\
& \equiv\left(\frac{\lambda}{n \cdot \mu}\right)^{r_{\max }+1}=1-\frac{p}{100} \\
& \equiv r_{\max }+1=\frac{\ln \left(1-\frac{p}{100}\right)}{\ln \left(\frac{\lambda}{n \cdot \mu}\right)}
\end{aligned}
$$

\{from Eq. 6 \}

$$
\begin{aligned}
& \equiv \frac{\omega_{p}-d_{1}}{d_{1}+d_{2}+\Delta}+1=\frac{\ln \left(1-\frac{p}{100}\right)}{\ln \left(\frac{\lambda}{n \cdot \mu}\right)} \\
& \equiv \omega_{p}=d_{1}+\left(\frac{\ln \left(1-\frac{p}{100}\right)}{\ln \left(\frac{\lambda}{n \cdot \mu}\right)}-1\right) \cdot\left(d_{1}+d_{2}+\Delta\right)
\end{aligned}
$$

Hence, Eq. 1 is proved.
Theorem 2 (Response Time Distribution). If there are $n$ backends, if the requests are assigned to backends as per the RAND LB Policy, and the CDF of the request execution times is denoted by $C D F_{\text {exe }}(x)$, then the probability that the response time of a request is less than or equal to $R T$ is given by

$$
\begin{equation*}
\sum_{r=0}^{r_{\max }}\left(\frac{\lambda}{n \cdot \mu}\right)^{r} \cdot\left(1-\frac{\lambda}{n \cdot \mu}\right) \cdot C D F_{\text {exe }}\left(R T-W T_{r}\right) \tag{7}
\end{equation*}
$$

where $_{\text {max }}=\left\lfloor\left(R T-d_{1}\right) /\left(d_{1}+d_{2}+\Delta\right)\right\rfloor$ and $W T_{r}=r \cdot\left(d_{1}+d_{2}+\Delta\right)+d_{1}$.
Proof. Let $Y$ and $Z$ denote the random variables corresponding to request execution times and waiting times, respectively. Let $R=Y+Z$ denote the random variable corresponding to the request response time. Thus, by the general formula for the distribution of the sum of two independent discrete variables:

$$
P(R \leq R T)=\sum_{z=-\infty}^{\infty} P(Z=z) \cdot P(Y \leq R T-z)
$$

\{since $Z$ can only take discrete values based on the number of retries, i.e., for $r$ retries, $Z=W T_{r}=r \cdot\left(d_{1}+d_{2}+\Delta\right)+d_{1}$, and since $r$ varies from 0 to $\infty$ \}

$$
P(R \leq R T)=\sum_{r=0}^{\infty} P\left(Z=W T_{r}\right) \cdot P\left(Y \leq R T-W T_{r}\right)
$$

$\left\{\right.$ since $R, Y, Z$ are non-negative, $R \leq R T$ implies that $Z=W T_{r} \leq R T$, which in turn implies that $\left.r \leq r_{\text {max }}=\left\lfloor\left(R T-d_{1}\right) /\left(d_{1}+d_{2}+\Delta\right)\right\rfloor\right\}$

$$
P(R \leq R T)=\sum_{r=0}^{r_{\max }} P\left(Z=W T_{r}\right) \cdot P\left(Y \leq R T-W T_{r}\right)
$$

$\left\{\right.$ since $P\left(Z=W T_{r}\right)$ is equivalent to $P_{r}=\left(P_{b u s y}\right)^{r} \cdot P_{\text {idle }}$ in Eq. 4, and since $P_{\text {busy }}=(\lambda) /(n \cdot \mu)$ and $P_{\text {idle }}=1-(\lambda)(n \cdot \mu)$ for the RAND LB Policy\}

$$
\begin{array}{r}
P(R \leq R T)=\sum_{r=0}^{r_{\max }}\left(\frac{\lambda}{n \cdot \mu}\right)^{r} \cdot\left(1-\frac{\lambda}{n \cdot \mu}\right) \\
\cdot P\left(Y \leq R T-W T_{r}\right)
\end{array}
$$

\{since $P\left(Y \leq R T-W T_{r}\right)$ is equivalent to the CDF of the execution time distribution\}

$$
\begin{aligned}
P(R \leq R T)=\sum_{r=0}^{r_{\max }}\left(\frac{\lambda}{n \cdot \mu}\right)^{r} \cdot\left(1-\frac{\lambda}{n \cdot \mu}\right) \\
\cdot C D F_{\text {exe }}\left(R T-W T_{r}\right) .
\end{aligned}
$$

Hence, Eq. 7 is proved.

