Thank you for your valuable review.

RQ1: The motivation lacks evidence to convince that significant variations in user traffic are not rare.

To assess the fluctuations in user traffic across different days, we first define the traffic fluctuation rate as:

$$FR_n = \left|\frac{r_n - r_{n-1}}{r_{n-1}}\right|$$

where r_n is the user traffic of day n. We have tracked daily user traffic on other common used recommendation datasets:

	FR >10% days/ all days	FR >10% days ratio	maximum fluctuation rate
KuaiRand-1K	13/30	43.33%	722.30%
industrial	4/7	57.14%	134.80%
Amazon_Baby	13/31	41.94%	722.57%
Amazon_Beauty	1926/3897	49.42%	1100.00%
yelp	3546/5317	66.69%	2200.00%

From the table, it is evident that the proportion of days with traffic fluctuation exceeding 10% is above 40% across all datasets, with the highest fluctuation rate reaching 2200%.

RQ3: Wrongly put the research line in related work.

Thank you for your suggestion. We will modified paper name to 'Ensuring Minimum Exposure for Providers Under Fluctuating User Traffic: A Robust Model'

The related work corresponding to minimum exposure guarantee fairness will be modified to:

Recently, fairness in re-ranking has become a hot topic in multi-stakeholder recommendation platforms [1, 2]. In two-sided platforms containing users and providers, fairness can generally be divided into: user-side fairness [9, 8], provider-side fairness [17, 18, 14, 15], and two-sided fairness [16, 13, 6, 12, 7]. There are different provider fairness forms: max-min fairness [17, 18]; equity of attention [16, 4, 12, 11]; minimum exposure guarantee (MEG) [13, 3, 10]. In this paper, we mainly consider minimum expo- sure guarantee fairness. In the minimum guarantee fairness research line, FairRec [13] and its extension FairRec+ [5] proposed an offline approach to *ensure the minimum exposure guarantee for providers while envy-free fair- ness for users. [10] proposed an Integer-Linear-Programming framework to ensure MEG considering position bias. Ben-Porat et.al [3] proposed and contextual multi-arm bandit approach considering a dynamic provider-fair setting in RS (i.e., provider receiving less than the MEG in an interval will leave the platform). However, none of these papers consider the practicality of the provider MEG fairness algorithm in user traffic fluctuation scenarios, leading to difficulties in applying fairness algorithms in real industrial settings.*

RQ4: How to set how to set m_p? Should it be user-traffic dependent?

We conduct experiments to verify the effectiveness of our methods RPF and the baselines under different m_p values. The experimental result is shown below

m_p	100		200		500		1000	
	Top5							
	NDCG@K	CV@K	NDCG@K	CV@K	NDCG@K	CV@K	NDCG@K	CV@K
P-MMF	0.9581	0.0016	0.9320	0.0022	0.9170	0.0024	0.9029	0.0017
TFROM	0.9053	0.0025	0.9053	0.0025	0.9053	0.0025	0.9053	0.0025
Prop	0.9641	0.0017	0.9618	0.0017	0.9610	0.0020	0.9605	0.0016
RPF	0.9618	**0.0006**	0.9612	**0.0006**	0.9607	**0.0008**	0.9604	**0.0007**
Improv.(%)	-0.2386	**-67.2009**	-0.0612	**-63.1077**	-0.0305	**-57.1677**	-0.0105	**-56.9893**
	Top10							
	NDCG@K	CV@K	NDCG@K	CV@K	NDCG@K	CV@K	NDCG@K	CV@K
PCT	0.8164	0.0038	0.8124	0.0034	0.8084	0.0036	0.8023	0.0031
P-MMF	0.9923	0.0015	0.9610	0.0011	0.9503	0.0016	0.9493	0.0010
TFROM	0.9885	0.0024	0.9885	0.0024	0.9885	0.0024	0.9885	0.0024
Naive	0.9952	0.0007	0.9947	0.0007	0.9919	0.0009	0.9891	0.0010
Prop	0.9919	0.0006	0.9899	0.0005	0.9865	0.0005	0.9848	0.0005
RPF	0.9956	0.0005	0.9954	0.0005	0.9944	0.0005	0.9916	0.0004
Improv.(%)	**0.3693**	**-11.8858**	**0.5562**	**-3.8575**	**0.8027**	**-2.0096**	**0.6869**	**-11.4880**

Top20								
	NDCG@K	CV@K	NDCG@K	CV@K	NDCG@K	CV@K	NDCG@K	CV@K
PCT	0.9402	0.0015	0.9392	0.0015	0.9382	0.0015	0.9342	0.0015
P-MMF	0.9926	0.0004	0.9927	0.0004	0.9652	0.0004	0.9652	0.0005
TFROM	0.9458	0.0017	0.9458	0.0017	0.9458	0.0017	0.9458	0.0017
Naive	0.9941	0.0005	0.9945	0.0005	0.9919	0.0006	0.9898	0.0006
Prop	0.9945	0.0005	0.9945	0.0006	0.9929	0.0006	0.9927	0.0006
RPF	0.9946	0.0004	0.9942	0.0004	0.9941	0.0004	0.9929	0.0004
Improv.(%)	**0.0127**	**-30.3021**	-0.0341	**-27.8251**	**0.1129**	**-27.0306**	**0.0204**	**-27.9468**

The blacked number means RPF outperforms all baselines that achieve 100 ESP%. Note that a higher NDCG@K is better, and a lower CV@K is better.

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