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Interactions Between Train Velocity and Cellular Link Throughput - An Extensive Study

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Abstract—Providing reliable internet connectivity to train passengers can be handled with onboard aggregation routers that use multiple external antennas to simultaneously convey user traffic over multiple links. This work studies the operational characteristics of a large-scale deployment of such a system. The examination focuses on how train velocity is associated with achieved link throughput, and how various interaction effects influence the relationship. A large data set collected over three years is analyzed, indicating that there is a systematic association between train velocity and link throughput that varies over the radio conditions and which is also linked to differences between operators.

I. INTRODUCTION

Travel by train is increasing in many parts of the world. While performing a train journey, many passengers find it convenient to be able to access the Internet for work or entertainment. However, providing service to a large number of passengers onboard a train traveling at high speed presents a challenging task for cellular networks [1], [2]. Various approaches have been considered for providing Internet access onboard trains [3], [4]. In this work we focus on systems which aggregate traffic from many users onboard a train. In particular, we here examine a system which provides WiFi access inside the train carriages, and aggregates this traffic through a specialized router using multiple cellular connections with external antennas. Such systems are in operation by a range of train operators. In this work we examine the operational characteristics of one large-scale deployment of such a system. In particular, this work focuses on the interrelationship between achieved cellular link throughput and train velocity.

Previous work [5] has indicated that the association between train velocity and link throughput is not steady over varying radio conditions. Examination of the relationship between train velocity and link throughput at different RS-SINR suggested sigmoid-like behavior where the association changed from negative to positive at a point around 12dB. The analysis in [5] was primarily carried out from a per train vantage point using a smaller data set. By performing a deeper analysis on a larger

data set collected over three years we provide further insights on the interrelationship between multiple factors associated with the link between train velocity and link throughput. Our analysis shows that the radio dependent effects are present also in the larger data set when analyzed from a per train or per train line perspective, but that there are significant differences when examining the data from a per operator perspective. Furthermore, analyzing the data from a per cell perspective indicates no radio related effects, which suggest that the MIMO and propagation based explanatory sketch put forth in [6] may not be sufficient to fully explain the observed behavior.

The remaining parts of the paper are organized as follows. We discuss related work in Section 2. Our data set is introduced in Section 3 while our analysis is presented in Section 4. This is followed by a discussion and conclusions in Sections 5 and 6, respectively.

II. RELATED WORK

Due to the complexities of modern cellular systems such as LTE, as well as the numerous diverse environmental conditions, there are a large number of factors that can potentially affect the association between train velocity and achieved link throughput. Fernandez et al. [7] present a survey of environmental effects particular to wireless communication in an railway setting. There have been a number of high-speed train radio channels measurement campaigns conducted, for which Wang et al. [8] provide a survey. Detailed active characterization of train LTE characteristics have been performed by Dominguez et al. [9] using a test train which performs several trial runs towards an eNodeB under their control.

In relation to the previous work on train velocity and throughput interaction by Garcia et al. [5] this work considers a much larger data set, and performs a considerably more fine-grained analysis also considering individual rail lines, different operators, passenger amounts, and characteristics for individual cells.

The effect of MIMO in relation to train velocity was first noticed in early LTE train measurements reported by Alasali et al. [10].

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Figure 1: Histograms of the most relevant metrics

III. DATA COLLECTION

Figure 2: Train lines used in evaluation

The examined data has been collected in 2016-2018 onboard 102 trains operating in the Swedish railway system. The Internet access routers onboard these trains log operational data at five second intervals. The collected data is comprised of train related characteristics such as GPS position, bearing, and train velocity. Furthermore, for each of the four modems in the aggregation router, radio-link metrics are recorded together with per link throughput and ping delay measurements.

We have implemented a data processing system which based on the collected data identifies train routes, and maps the recorded data into train journeys along one of the identified train routes. For this examination the six routes which have the highest number of observations were selected to be included in the continued analysis. The characteristics of these six routes are presented in Table I. The outline of the six train lines going between

Route name	Route Length	Nr of journeys	Nr router ids	Nr of cell-ids	Avg velocity
GbgSto2	453 km	16039	58	2736	142 km/h
GbgSto1	485 km	14610	76	3865	101 km/h
MalSto0	614 km	10327	39	3336	136 km/h
StoUme0	709 km	3565	19	3402	109 km/h
KsdSto0	324 km	7378	57	2104	130 km/h
GbgKsd1	249 km	7527	13	1253	100 km/h
Overall		59446	102	12311	121 km/h

Table I: Examined train lines

the cities of Stockholm, Gothenburg, Malmö, Karlstad

and Umeå is shown in Figure 2. For these six lines, a total of around 650 million observations were collected.

An initial examination of the data set was performed, indicating the presence of some overly high train velocities, unexpected zero values for some radio metric readings, and some other data collection anomalies. A set of data filtering expressions were implemented to remove inconsistencies from the data, see Table II for details. The filtering expression either removes an observation (O) or the entire train journey for which an anomalous observation was found (J). While the data set contains data for the four links at each observation time, we only consider data for the link with the highest throughput. As the data is passively collected, it is not possible to ensure that the observed link throughput reflects the limits of the cellular network rather than a lack of aggregate user demand, and at times not all links will be performing data transfer. For the continued analysis, only the throughput values of the link with highest throughput are considered in the analysis. After the filtering steps the data set consists of around 160 million remaining observations across 59446 train journeys.

Observation Filters	Journey Filters
Not an LTE connection (O)	Train velocity > 65 m/s or NaN (J)
Connection unavailable (O)	hw not MC7710 (J)
ping > 10000ms (O)	max(pa) < 10 (J)
Link bw < 5 Mhz (O)	journeytime > 30% over median (J)
Not Op1 or Op2 (O)	

Table II: Data filtering expressions

IV. DATA ANALYSIS

A subset of the most relevant metrics contained in the data set is shown as histograms in Figure 1, where also the minimum / mean / median / maximum values are given. The distribution of number activated devices ('pa'), i.e. where the user have accepted the terms of usage, is shown in the leftmost histogram, followed by the distribution of observed train velocities. As the train is regularly stopping at train stations during its journey, the distribution shows a spike at zero velocity. Of the recorded radio metrics, reference signal-signal to noise and interference ratio (RS-SINR), is used as an indicator of radio conditions. RS-SINR measures the average power contributions of LTE resource elements

that carry reference signals, divided by the noise and interference of such elements as defined in [11]. As seen in Figure 1, the observation count for RS-SINR is lower than for the other metrics since the modems report RS-SINR values less frequently than other data is collected. The rightmost histogram shows l_tp_{rx} , which is the achieved link throughput for the link with highest link throughput at the observation time.

A. Train velocity and link throughput

We take an interest in the relationship between train velocity and link throughput, and this can be illustrated in a scatter plot. Various groupings of the complete data set can be performed and Figure 3 shows a scatter plot for the observations belonging to a particular train. Clearly, there is no apparent strong correlation between the two metrics. On the set of observations in the plot, a linear regression fit can be made to explore potential association between train velocity and link throughput. As the number of observations is large, an estimate of the velocity and throughput (v-tp) slope value with low spread can be obtained.

Figure 3: Scatter plots between link throughput and velocity for one train

While the data shown in Figure 3 represents only one train, similar graphs can be constructed for all trains in the data set with more than a minimum number of observations (here set to 10000). Further, the data for each train can be split into bins representing the reported radio conditions for the different observation as indicated by the RS-SINR value. Thus, there will for each train be a sequence of v-tp slope values, each associated with a RS-SINR value. The sequence of the v-tp slope values for 23 trains in the 6 month data set previously examined in [5] is shown in Figure 4a. Only values for observations that had at least 150 active devices are considered in order to maximize the possibility that the achieved link throughput is limited by link capacity instead of aggregate demand. Also included in the figure is a fit of a sigmoid function in the form of a generalized logistic function:

$$S(R) = \frac{S_s}{1 + e^{-R_s*(R-R_0)}} + S_0 \quad (1)$$

where S_x corresponds to slope related parameters, and R_x to RS-SINR related parameters. Fitting of the sigmoid model parameters S_0, S_s, R_0, R_s is done using

(a) Previous 6 mth data, per train [5]

(b) New data, per train

(c) New data, random grouping

(d) Global sigmoid fit, linear regression and akima interpolation

Figure 4: Variations on the computation of slope coefficient for link throughput versus velocity over RS-SINR bins

non-linear Levenberg-Marquardt least-squares regression [12]. The sigmoid fitted in Figure 4a crosses the zero point of the slope coefficient at an RS-SINR slightly above 12 dB.

The same computations were performed for the new data, with the results shown in Figure 4b. While there is a positive trend in the slope as radio conditions improve the v-tp slope values are somewhat shifted downwards. Also noticeable is the amount of variation observed for different trains. Partitioning the data by trains represent one possible grouping of the underlying data and may achieve reduced variance if there are considerable variation between the characteristics of different trains. As an alternative, the data can be partitioned randomly into the same number of groups and it can be observed in Figure 4c that doing so decreases the amount of vari-

Figure 5: Slope coefficient for Train velocity versus link throughput over RS-SINR bins across six train lines

Figure 6: Slope coefficient for Train velocity vs. link throughput over RS-SINR bins across six train lines, per operator (Operator 1: Cyan and magenta. Operator 2: Blue and green.)

ability while the overall trend of the data remains. When grouped on individual trains, the amount of underlying data points used to compute each v-tp slope may vary considerably thus contributing to increased variability in the resulting v-tp slope values. With random grouping all v-tp slope values are calculated using approximately the same number of underlying observations. What is of prime interest here is the overall rather than train-specific behavior, and the following results will focus on values presented without per-train grouping. Figure 4d shows the same fitted sigmoid as in Figure 4c, and also a curve interpolation performed using the Akima method [13], here shown as a thick yellow line. Such interpolation allows the trends of the underlying data to be shown without imposing a sigmoid model structure to the data. Also shown is a linear regression of the v-tp slope values across the RS-SINR bins. From such linear regression, a second-order sinr-vtp slope value can be computed, and it will be considered in some of the later evaluations.

B. Per train line variation

The results presented in the previous graphs are based on the six train line data set, considering all measurements that reported more than 150 active devices

(i.e $pa > 150$) similar to the approach of the previous study [5]. The data set in this study is larger, and we now also consider an analysis on a per train line basis. As there is quite some variation in the number of passengers in the different train lines, the aggregate load filtering level is set to $pa > 100$, to ensure that there are sufficient number of observations for the two train lines with the fewest passenger count. The results per train line are illustrated in Figure 5. On each graph the number of underlying observations are listed, and it can be noted that the two train lines (GbgSto2, GbgKsd1) which have low passenger counts have markedly lower number of observations, even if one of them was the one with the largest number of overall observations (GbgSto2). Both of these lines have a factor of four less observations than any of the other train lines. Examining the behavior of the v-tp slope values it can be noted that both of these train lines (GbgSto2, GbgKsd1), while showing positive sinr-vtp slopes, did not show sinr-vtp zero crossing consistent with the sigmoid behavior observed in Figure 4. Also, the KsdSto1 line did not exhibit a sigmoid-consistent zero crossing. In summary these results indicate an association between train line

and the presence of sigmoid behavior. The sources of this association can not be comprehensively disentangled with the presently available data. However, there seems to be a connection to the amount of active devices (pa) and the presence of sigmoid-like behavior, in addition to train-line specific characteristics that may influence the v-tp behavior of each train line.

C. Per operator differences

Two different operators are utilized to provide cellular access to the trains while traveling. These operators may use equipment from different eNodeB hardware vendors, and may configure various aspects of their network differently. Thus, examining the data from a per operator perspective may provide useful insights. Figure 6 shows the data from the six train lines, but now split so that observations for the highest loaded link are split into two subsets: one subset for each of the two operators with a total of 5.0 million observations for Op 1 and 6.5 million for Op2. Examining the figure it can be seen that there is a noted difference between the operators, where for Op1 five out of six train lines show sinr-vtp slopes that are fairly flat and do not have a zero crossing. In contrast, for Op2 four out of six train lines show sigmoid-consistent sinr-vtp slopes, with the two low-passenger train lines being the exceptions. In particular, the KsdSto0 line which showed no clear sigmoid-behavior in Figure 5, here in Figure 6 illustrates that the the overall behavior can be decomposed into a Op2 behavior which is clearly sigmoid-consistent, and Op1 which is clearly not. Curiously, for Op1, StoUmu0 is an exception being the only Op1 line showing sigmoid-consistent behavior. StoUmu is the longest of the six lines, and also travels over sparsely populated regions to a considerably larger extent than the other train lines, which may impact network site allocations and network configurations.

D. Distribution over active device numbers

The data set is constructed using passive means, i.e. the metrics of interest are recorded while the system is in operational use, and the traffic demand comes from the aggregate passenger traffic demands. If the aggregate demand scheduled over the studied link is lower than the available link rate, then the reported link rate will be bounded by traffic demand rather than link characteristics. The previous characterization has been performed with a minimum threshold on the number of active devices, assuming that when the number of active devices is high the aggregate user demand would not be a limiting factor. How the number of active passengers affect the v-tp and sinr-vtp characteristics is relevant for further examination.

Thus, the data for Op2 and the four sigmoid-consistent lines as seen in Figure 6 is also examined from the perspective of quartiles of the number of activated devices at

Figure 7: Slope coefficients for quartiles of the 'activated devices' (pa) variable. q1: |, q2: x, q3: Δ, q4: □

each observation instance. The results are shown in Figure 7, with the boundaries of the quartile bins indicated above each graph. From the figure some observations can be made. While the first quartile (marked with |) shows some degree of inconsistency, for the remaining three quartiles there is a clear trend of decreasing v-tp slope values as the number of active devices increases, which is especially visible for lines MalSto0 and StoUmu0. The underlying mechanisms for this observed behavior cannot be derived only with help from the available data, but a notable aspect is that sigmoid-consistent behavior is observed also for the 2nd-4th quartiles hinting that the load limit of 100 or 150 active devices may have been conservative. Using a somewhat lower limit would allow slightly more observations from the data set to be considered in an analysis. Regarding the difference in observed inter-quartile spread between the more tightly spaced 2-4 quartiles for GbgSto1 and KsdSto1 as compared to the more spread out MalSto0 and StoUme0, we note that this difference also appears to be co-varying with cell density along the train line. A somewhat simplified metric that can be used to express such density is the average distance between cells which can be computed

Figure 8: sinr-vtp slope and zero crossing distributions for Op2-4line-4pa (a,b), and 48 most seen CellIDs (c,d)

based on the data in Table I. This metric would be 125m and 153m for GbgSto1 and KsdSto0, while for MalSto0 and StoUme0 it would be 184m and 180m.

E. Observed effect validation

Figure 7 shows the v-tp slope coefficients for Op1 over four considered routes divided across four quantile spans. This Op2-4Routes-4pa data set can also be used to compute sinr-vtp coefficients for each quantile and route combination, arriving at 16 sinr-vtp slope values. The zero crossing point where the sinr-vtp slope crosses the 0 mark on the y axis, i.e. the point where the association of increased velocity with reported link throughput goes from being negative to positive, is also considered. The distribution of these sinr-vtp slope values and zero crossings are shown in blue color in Figures 8a and 8b. To ascertain that the observed effects are not an artifact from the observation aggregation procedures performed to arrive at a sinr-vtp slope value, a permutation test was performed. The values of the link throughput were shuffled, and the regression computations was then done using this permuted data set. The distribution of the resulting 16 sinr-vtp slope and zero crossing values are shown in apricot color. Subsequent random permutations resulted in similar distributions with a sinr-vtp slope coefficient centered around zero. While a comprehensive explanation of all aspects of the observed v-tp sigmoid-like behavior remains elusive, the permutation test indicates that the observed effect is not spuriously occurring due to randomness or processing artifacts.

F. Per cell data evaluation

A further aspect of interest is to what extent a sigmoid-like behavior can be observed also at the individual cell level. To provide a globally unique identifier of LTE cells, the E-UTRAN cell global identification (ECGI) is defined [14, pg 83], and we use the ECGI to extract a unique cell id (CID) for use in a per cell analysis. The four train line data set used in Figure 7 was reused to additionally do a per CID analysis. The data set had observations of 4559 unique CIDs, and of these the 48 CIDs with the highest number of observations were considered. For each CID, the observations were binned into RS-SINR bins, and the v-tp slopes were computed for each bin. A sinr-vtp linear slope approximation was then computed, similarly as for the previous analysis. The characteristics of the 48 CID sinr-vtp slopes are shown in Figures 8c and 8d as the blue histograms. Neither the sinr-vtp slope coefficient, or the zero crossing show any strong inclination towards sigmoid-behavior. As a contrast, the same 48 CID data set was also examined by randomly partitioning it into 48 folds instead of partitioning it by CID, and the computations redone. As visible by the green histogram, the data is now consistent with sigmoid-behavior. A permutation of the link throughput data was also performed on the CID grouped data. The permuted results show a zero mean slope coefficient, and a spread out zero crossing distribution. It can be noted that slope coefficients close to zero tend to considerably spread out the corresponding zero crossings distribution even for small amounts of slope variations.

V. DISCUSSION

In [6] a potential cause contributing to the observed sigmoid-behavior is discussed, observing that the scattering environment surrounding the railway and MIMO implementation aspects in LTE could contribute to it. While the difference per operator might be consistent with such an explanatory model if the operators have different MIMO configuration settings, it would appear unlikely that sigmoid behavior would be absent from the examined CIDs to the extent observed here. In relation to the impact of train velocity on performance, [15] studies a case where SINR is 21 dB, and for the velocity range considered in our study (0-200 km/h) they report either no effect of velocity, or a negative v-tp slope (for higher channel quality indicator (CQI) numbers). However, their results were obtained from a LTE link testbed and not from traffic traversing an actual LTE network. Earlier, Merz et al. [16] have reported results from an active train mounted measurement campaign, identifying a non-negligible impact of train velocity although not with differences in the behavior over the RS-SINR ranges. A limited vehicular test campaign reported by Berisha et al. [17] noted the switch in MIMO rank from 1 to

2 at the same RS-SINR values as observed for the zero crossing in the current study (~10-16 dB).

When considering potential explanatory models for the observed behavior, it may be relevant to consider that the number of active devices connected to the onboard WiFi also can serve as a proxy for the number of UEs inside the train. A subset of these UEs will be engaged in voice connections (or data connections directly with the LTE network and not via the WiFi router relay). Such UEs need to engage the base station in regular handover signaling, and higher train velocity corresponds to more handover signaling per time unit. A more detailed examination of the measurements for small number of cells showed that there are also a number of cases where the geography and radio propagation factors induces not one but several sequential handovers between neighboring cells.

A cursory examination for the existence of time non-stationarity of the data was done, and while indications of time-variability was at hand a more complete analysis would require to account for time-dependent travel patterns over vacation periods and holidays. A further examination of time-variation is left for future work.

VI. CONCLUSIONS

Providing cellular access to a large number of users onboard a train traveling at high speed is a challenging task for cellular networks. This work performs a large-scale analysis of operational data collected over three years from a fleet of trains with cellular access routers that provide Internet connectivity to train passengers. In particular, the study examines the association between train velocity, and achieved link throughput. While there are numerous factors that affect the achieved link throughput at any instance, the results indicate that there is a systematic association between train velocity and link throughput that varies over the radio conditions. While clearly present in the data set, the presence of such effect is further linked to differences between operators and is surprisingly enough not visible on an individual cell level. This suggests that enhanced explanatory models are needed to fully explain the effect.

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REFERENCES

- [1] M. K. Müller, M. Taranetz, and M. Rupp, "Providing current and future cellular services to high speed trains," *Communications Magazine, IEEE*, vol. 53, no. 10, pp. 96–101, 2015.
- [2] J. Wu and P. Fan, "A survey on high mobility wireless communications: Challenges, opportunities and solutions," *IEEE Access*, vol. 4, pp. 450–476, 2016.
- [3] É. Masson, M. Berbineau, and S. Lefebvre, "Broadband Internet access on board high speed trains, A technological survey," in *Communication Technologies for Vehicles*. Springer, 2015.
- [4] D. T. Fokum and V. S. Frost, "A survey on methods for broadband internet access on trains," *Communications Surveys & Tutorials, IEEE*, vol. 12, no. 2, pp. 171–185, 2010.
- [5] J. Garcia, S. Alfredsson, A. Brunstrom, and C. Beckman, "Train velocity and data throughput-a large scale LTE cellular measurements study," in *2017 IEEE 86th Vehicular Technology Conference (VTC-Fall)*. IEEE, 2017, pp. 1–6.
- [6] C. Beckman, J. Garcia, S. Alfredsson, and A. Brunstrom, "On the impact of velocity on the train-to-earth MIMO propagation channel: Statistical observations and qualitative analysis," in *2017 IEEE International Symposium on Antennas and Propagation & USNC/URSI National Radio Science Meeting*. IEEE, 2017, pp. 1865–1866.
- [7] N. Fernandez, S. Arrizabalaga, J. Añorga, J. Goya, I. Adín, and J. Mendizabal, "Survey of environmental effects in railway communications." in *Nets4Cars/Nets4Trains/Nets4Aircraft*. Springer, 2018, pp. 56–67.
- [8] C.-X. Wang, A. Ghazal, B. Ai, Y. Liu, and P. Fan, "Channel measurements and models for high-speed train communication systems: A survey," *IEEE communications surveys & tutorials*, vol. 18, no. 2, pp. 974–987, 2016.
- [9] T. Domínguez-Bolaño, J. Rodríguez-Piñero, J. A. García-Naya, and L. Castedo, "Experimental characterization of LTE wireless links in high-speed trains," *Wireless Communications and Mobile Computing*, vol. 2017, 2017.
- [10] M. Alasali, C. Beckman, and M. Karlsson, "Providing internet to trains using MIMO in LTE networks," in *2014 International Conference on Connected Vehicles and Expo (ICCVE)*, Nov 2014, pp. 810–814.
- [11] 3GPP, "Evolved Universal Terrestrial Radio Access (E-UTRA); Physical layer; Measurements," 3rd Generation Partnership Project (3GPP), Technical Specification (TS) 36.214, Jul. 2018, version 15.2.0 Release 15.
- [12] J. J. Moré, "The levenberg-marquardt algorithm: Implementation and theory," in *Numerical Analysis*, ser. Lecture Notes in Mathematics, G. Watson, Ed. Springer, 1978, vol. 630, pp. 105–116.
- [13] H. Akima, "A new method of interpolation and smooth curve fitting based on local procedures," *J. ACM*, vol. 17, no. 4, pp. 589–602, Oct. 1970.
- [14] 3GPP, "Universal Mobile Telecommunications System (UMTS); Numbering, addressing and identification," 3rd Generation Partnership Project (3GPP), Technical Specification (TS) 23.003, Oct. 2018, version 15.5.0 Release 15.
- [15] J. Rodríguez-Piñero, P. Suárez-Casal, M. Lerch, S. Caban, J. A. García-Naya, L. Castedo, and M. Rupp, "LTE downlink performance in high speed trains," in *Vehicular Technology Conference (VTC Spring), 2015 IEEE 81st*. IEEE, 2015, pp. 1–5.
- [16] R. Merz, D. Wenger, D. Scanferla, and S. Mauron, "Performance of LTE in a high-velocity environment: A measurement study," in *Proceedings of the 4th workshop on All things cellular: operations, applications, & challenges*. ACM, 2014, pp. 47–52.
- [17] T. Berisha and C. F. Mecklenbräuker, "2D LOS/NLOS urban maps and LTE MIMO performance evaluation for vehicular use cases," in *2017 IEEE Vehicular Networking Conference (VNC)*. IEEE, 2017, pp. 291–294.