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Propagation channel assessment for GEO feeder links

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Abstract—Seen as the essential infrastructure supporting future high-throughput space data highways, Optical Feeder Links are still confronted with the need to manage atmospheric disruptions. Complex correction methods, including adaptive optics (AO), coding, interleaving and handover will be necessary to ensure the high link availability expected from a data providing service. Each of these correction methods might reap the benefits of an accurate propagation channel assessment either for real time optimization to feed control laws of the AO for short-term optimization in a minute timescale and for longer-term, typically dozen of minutes to few hours, to supervise the handover process. We present here the principal characteristics of ONERA's optical ground station FEELINGS data pipeline and draws perspectives on its exploitation for link availability prediction.

Index Terms—Optical ground station, adaptive optics, optical feeder link

I. INTRODUCTION

Considered as the backbone of future very high throughput space data highways, Optical Feeder Links are currently being pushed a step forward to high data rate demonstrations. Their development is however still highly dependent on the possibility to adequately mitigate atmospheric channel impairments

with a reasonable complexity. This is particularly challenging due to the variability of atmospheric conditions to be faced for future Optical Ground Stations (OGS) locations, as the optical quality of the site is not necessarily the only criterion of choice.

The strategies developed to mitigate the propagation channel impact are based on complex correction methods (adaptive optics (AO), interleaving and coding) whose design must be optimized according to propagation conditions to keep reasonable costs. The ability to anticipate channel impairments is of critical importance in the very short term (typically for few minutes) to adjust the configuration of the correction methods, and for a longer timescale (few dozen of minutes) to optimize the routing of information through the network and enable the handover process required to overcome cloud masking.

Thanks to their built-in system the future high data rate OGS can benefit from a unique metrology to characterize the propagation conditions along the line of sight. The use of a dedicated data pipeline and simplified performance model give access to a real-time theoretical performance assessment

during the optical links. Using machine learning tools, the estimated atmospheric parameters can be used to predict short-term atmospheric conditions and performance over duration up to one hour, thus paving the way to an optimized operation of the ground station network accordingly.

We present here an approach to exploit the data of the wavefront sensor allowing the estimation of key turbulent parameters along the line of sight. Based on the exploitation of a metamodel trained on the results of numerical weather prediction models, we investigate the possibility of predicting the key atmospheric turbulence parameters for optical communication identified in [1] using the latest deep learning models dedicated to time series forecasting. The tools presented here will constitute the core of the data processing pipeline implemented in ONERA's OGS FEELINGS [2]. Its first light is scheduled for the end of 2023, with the potential to establish the first links with a GEO satellite in 2024 [3].

II. OPTICAL FEEDER LINK PERFORMANCE ASSESSMENT

A. Different needs for different timescales

The turbulence's impact is critical for both downlinks, for injection optimization, and uplinks, due to the influence of anisoplanatism and partial correction. Therefore, performance evaluation at different time scales is essential. In the short term, it is compulsory to optimize various subsystems, especially the AO system. This optimization implies a fine-tuning of the parameters such as wavefront sensor thresholds and background management, as well as the control law parameters (including modal gains and matrices in the case of predictive control law) which relies on a performance evaluation within short execution times (typ. on the order of a few tens of seconds, in accordance with typical stationarity durations). In the mid-term, there is a need to anticipate the operational conditions at alternative sites we might switch to in the event of cloud interruptions, turbulence conditions exceeding the operating point, or proximity of the sun with the line of sight. This implies to forecast turbulence conditions with time horizons of the order of an hour or more.

Therefore, the dual challenge lies in achieving both short-term performance assessment with high precision and mid-term turbulence condition forecast, which necessitates dealing with different time scales and their associated complexities.

Concerning the short term scale, the performance evaluation strategy relies on using a Monte Carlo model (the Statistical AO System Testing (SAOST) model [4]), enabling the generation of statistical and temporal characteristics to establish an instantaneous performance metric (with a temporal scale of turbulence stationarity, typ. up to a minute). The Monte Carlo model takes as input elements of the communication link budget (see II-C) and parameters measured by the station's instrumentation. The conditions of turbulence play a crucial role in evaluating the performance of the system making their accurate evaluation essential for the overall performance assessment process.

For the long term scale, it is possible to replace the SAOST model with a metamodel based solely on integrated turbulence

parameters. The key idea is to accurately predict the integrated parameters using weather prediction database to access to a performance forecast. This transition to a metamodel simplifies the performance prediction process by relying exclusively on these integrated turbulence parameters.

B. Data pipeline structure

The station's objectives and structure are presented in [5]. The station's various instruments will generate large quantities of data during the acquisitions. All the various sensors and instruments provides data concerning the state and health of the OGS subsystems and the surrounding instruments (weather station). They monitor the health of the station and can trigger emergency processes.

The second part concerns the data received by the fibre detector, which digitises the time series of the received flux from the satellite. The mean and variance of these series are calculated for comparison with the estimated values.

The last part of this data is acquired to feed the performance estimation simulator and understand the limits of the instrument. A weather station close to the ground station is used to acquire measurements of temperature, wind, humidity, pressure and, under certain conditions, Fried's parameter and the scintillation rate. The software process this data to estimate the turbulence profile (see section II-D), the wind profile and the atmospheric transmission in order to numerically estimate the performance of the link. The profiles are estimated from the Shack-Hartmann measurements. These estimated turbulence conditions feed the ONERA's SAOST model [4] which provides statistics on the time series of flux received on the ground and at satellite level.

The experimental statistics are then compared in real-time to theoretical signal statistics, computed through SAOST model. This model uses a Monte-Carlo approach on an ideal AO error budget. It takes into account fitting error, aliasing error, temporal error, PAA induced anisoplanatism error, turbulent phase residuals and power in the bucket power fluctuations induced by scintillation. It allows to compute statistical series with a high number of occurrences quickly, and thus has good statistical convergence. However it doesn't include a precise description of AO components, such as the wavefront sensor or the deformable mirror.

In order to get an even higher level of understanding of the performance and the channel characteristics, this data pipeline is tested and compared to a digital twin currently under development. The latter includes the ONERA's PILOT software to simulate the propagation of an optical wave through the atmosphere, as well as an AO module for ground-satellite links. It is gradually being improved to take into account more and more effects linked to the specific characteristics of the OGS and the links. This is a precise, end-to-end model whose calculation time is incompatible with the ground station's real time data processing requirements.

C. Link budget and performance metrics

Setting up a high-speed data transmission requires being able to guarantee that the detection signal-to-noise ratio is

maintained above a certain threshold for the duration of the data transmission. This means establishing a balance of the attenuations suffered by the transmitted wave from transmission to reception. The viability of this balance depends on the information transmission capacity.

We provide in Table 1 an example of link budget obtained in the case of GEO-FL for the uplink and the downlink. The wavelength is supposed to be C-Band. In this table, we considered that the OGS contributions are those of the FEELINGS ground station [5]. For the payload, we suppose here 1 W of emitted power through a 25 cm diameter aperture [6], but of course it will depend on the targeted satellite. For instance, HICALI is 2.5 W optical power in C-band for a 15 cm diameter aperture [7], while ALPHASAT is up to 4 W emitted power through a 30 cm diameter aperture at 1.06 μm [8].

| | | Uplink | Downlink |
|---|-----|---------|----------|
| Tx diameter | m | 0,6 | 0,25 |
| Tx power | dBm | 47 | 30 |
| Tx antenna gain | dB | 119,48 | 114,1 |
| Tx optical loss | dB | -3,4 | -3 |
| Tx pointing loss | dB | -1,68 | -0,7 |
| Geometrical loss | dB | -289,85 | -289,85 |
| Absorption/ aerosol loss | dB | -0,4 | -0,4 |
| Cloud margin | dB | -4,4 | -4,4 |
| Turbulence and AO correction (95% of availability) | dB | -4,9 | -1,9 |
| Rx diameter | m | 0,25 | 0,6 |
| Rx antenna gain | dB | 114,1 | 119,48 |
| Rx optical loss | dB | -3 | -2,8 |
| Total Rx power | dBm | -27,05 | -39,47 |
| Mean sensitivity (10-3) BPSK | dBm | -44,5 | -44,5 |
| Overall margin | dB | 17,45 | 5,03 |

Fig. 1. Example of FEELINGS-GEO uplink and downlink link budget. For more information about the chosen data, see section II-C.

The mean sensitivity value for BPSK used in the table assumes a 10 Gbps BPSK signal, for a targetted BER of 10^{-3} and a space-grade high gain fiber amplifier in the detection chain [9].

As for the channel, the turbulence conditions and atmosphere we consider in this table are chosen to be representative of medium cases - i.e. we expect the conditions to be better (or worse) than these values half of the time (by day time).

The values contained in that table will have to be confronted to experimental data. Channel properties will be estimated through the post-processing of AO data for turbulence and wind speed (see section II-D), and through post-processing of terrain measurements for transmission (all-sky camera, weather station, lidar, photometer...); performance metrics will be mean signal and signal standard deviation.

The goal is to establish an error budget during the acquisitions and compare it with the received flux.

D. Turbulence channel characterization

The estimated losses introduced by atmospheric turbulence after correction or precompensation by AO are calculated from a turbulence profile estimated from the Shack-Hartmann data. To be effective, the accuracy of the method used to estimate the profile must be such that the difference between the performance obtained with the estimated profile and the one obtained with the real profile is negligible compared with the link margin.

Since turbulence conditions are highly dependent on local environmental configuration (local wind flows and surface emissivity), the most relevant way to assess properly turbulence impact on the line of sight is to extract the C_n^2 profile directly from data extracted from the AO loop concomitantly to the acquired AO compensated signal. The method exploited here has been proposed 15 years ago [10] and validated in comparable turbulence conditions for slant path propagation [4], [11]. The method consists in estimating the C_n^2 profile from the numerical inversion of a direct model describing the spatial correlations of slopes and intensities measurements in the Rytov regime according to a principal analogous to the one exploited in the SHIMM instrument [12]. The precision of the estimation depends on the choice of different key parameters. The number of occurrences from which the empirical covariances are calculated will affect the precision of the covariance evaluation (convergence noise). The propagation path sampling will affect the accuracy with which the direct model represents the effective turbulence profile. The noise on both slopes and intensity measurements might degrade the covariance estimation introducing a bias on the variance estimation. Most of these parameters also affect the computation time and therefore the periodicity with which such an estimation can be performed.

We evaluate here the impact of the C_n^2 profile sampling and noises on the propagation channel fluctuations for the AO precompensated uplink. In this aim, a 10 s time series of slopes and intensities provided by a 17×17 Shack-Hartmann wavefront sensor (SHWFS) sampling a 60 cm aperture at a 1 kHz frequency is generated using an end-to-end simulation on a known profile. The known profile is taken from the MOSPAR database [4], [13] so that it presents a 70% joint cumulative probability for r_0 and for the isoplanatic angle θ_0 : 70% of the profiles of the database present a greater r_0 and a greater θ_0 than the one of the profile considered here. The integrated turbulence parameters for the MOSPAR7070 are reported in the first row of table I. The wind profile used for the simulation is a Bufton one with 10 m.s^{-1} for the ground speed parameter and 30 m.s^{-1} for the high altitude layer. Both photon noise and detector noise generated by the detection process are taken into account, and the potential saturation of the detector as well. The incoming irradiance in the overall aperture is 5.5 nW, the noise detector standard deviation is $\sigma_{noise}^2 = 30$ electrons and the sensor is assumed to have a 0.75 quantum efficiency. The detector has a 43 kilo-electrons well capacity and have a linear response. Using the SHWFS data

TABLE I
INTEGRATED TURBULENCE PARAMETERS FOR THE DIFFERENT PROFILES.

| Profile | r_0 [cm] | θ_0 [μ rad] | σ_χ^2 |
|------------|------------|-------------------------|-----------------|
| MOSPAR7070 | 5.8 | 9.3 | 0.047 |
| 29 layers | 5.8 | 9.3 | 0.047 |
| 12 layers | 5.6 | 9.2 | 0.037 |
| 4 layers | 5.6 | 9.3 | 0.035 |
| 3 layers | 5.6 | 9.6 | 0.034 |

hence generated a C_n^2 profile estimation is performed from the empirical evaluation of the covariances via the iterative minimization of a maximum likelihood criterion under positivity constraint. The C_n^2 used to generate the simulated data is plotted in continuous black lines in figure 2. It consists in 29 layers with an irregular sampling adapted to the end-to-end simulation process. The result of the estimation assuming a spatial sampling of the turbulence identical to the one of the profile used for the simulations is in red. This case corresponds to an estimation only affected by the convergence noise, every other unknown parameter being known. The profiles obtained with a 12 layers, 4 layers and 3 layers evenly spaced are plotted in green, blue and purple respectively. For each profile the C_n^2 is supposed to be constant on the thickness of the layer. The true profile presents 4 major layers (ground, 7 km from the telescope, 16 km and 30 km along the line of sight). These layers appears very well estimated in the convergence noise limited case. This enables to estimate a sensitivity limit of the approach that appears around $5 \cdot 10^{-18} m^{-2/3}$. The 4 main layers contributions can be clearly identified for the 12 and 4 layers estimation case, contrary to the 3 layers one. The integrated parameters calculated from the profiles are reported in table I. Despite the 29 layers case which enables an accurate estimation of the three considered parameters, the other cases lead to small underestimation of r_0 (typ. 3%) and to a more significant underestimation of σ_χ^2 (21% for the 12 layers case). The isoplanatic angle evaluation remains precise unless for the 3 layers case.

In order to assess the impact of the different sources of errors simulated here (spatial sampling and noise) on the uplink propagation channel statistics we investigate the distribution of turbulence related atmospheric channel power attenuation by numerical modeling. Random draws of uplink channel power attenuation are calculated using a simplified performance model called SAOST, a Monte Carlo simulation tool exploiting random draws of complex amplitude maps and AO corrected phase residuals generated in the Fourier space. The cumulated probability evaluation provided with SAOST on 20000 independent occurrences is plotted figure 3 as a function of the attenuation threshold s for an AO precompensation of 17 Zernike radial orders at 2 kHz. The telescope diameter corresponds to the 60 cm of the FEELINGS ground station [14]. We consider the 10^{-3} cumulated probability as a manageable probability with respect to the error correcting codes typical recovery performance. For the 29 layers case the power attenuation threshold difference with the reference case (MOSPAR7070) is 0.15 dB, respectively 0.20, 0.45 and 0.95

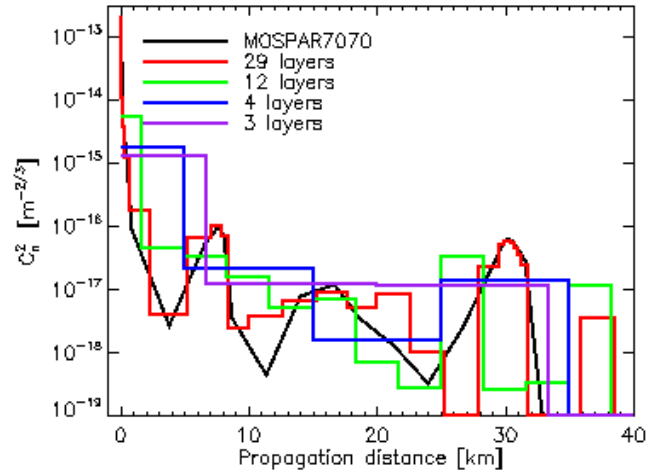


Fig. 2. C_n^2 profiles, MOSPAR7070 in black, 29 layers in red, 12 layers in green, 4 layers in blue, 3 layers in purple.

for the 12 layers, 4 layers and 3 layers case. For the 29 layers case the position of the layers are identical to those in the MOSPAR7070. The remaining errors that prevent the 10^{-3} attenuation threshold from being identical to the reference case are the limited number of occurrences in the statistical horizon to compute the empirical covariances and the influence of the noise on the Shack-Hartmann wavefront sensor data. The only additional error for the other cases is the number of layers used to describe the profile. This error increases as the number of layers decreases. In view of the undergone computational burden (it takes less than 30 s to perform the 12 layers estimation on a single CPU) and of the gain in terms of link margin uncertainty (0.25 dB compared to the 4 layers case) a 12 layers estimation will be implemented in FEELINGS' data pipeline.

We presented an evaluation of the power margin uncertainty related to the turbulence channel characterization for a typical GEO feeder link on the uplink. According to the results a 0.20 dB typical error can be expected from the C_n^2 profile estimation method exploited here. These results can be considered as a best case scenario, as they were obtained assuming that both the outer scale of turbulence and the wind profile are assumed to be known. As this is not the case in practice a dedicated process must be considered to estimate as well these parameters. For the outer scale influence, a way to proceed would be to extract it from a fit of the measured phase variance per radial order exploiting a direct model already available in the literature[15], [16]. For the wind profile, a short term approach could rely on a parametric estimation of a Bufton wind profile which parameters would be provided by local measurements (for the ground wind speed modulus) and for the unknown parameters on the minimization of an error criterion between the scintillation temporal power spectrum estimated from the SHWFS data and a model with an approach analogous to the one presented in [17]. Of course

on a longer term prospect a generalization of the C_n^2 profile estimation to a joint estimation of both the C_n^2 and wind profile should be made possible by the possibility to compute the spatio-temporal covariances of slopes and intensities in real time, assuming a tractable expression of these spatio-temporal covariances is available.

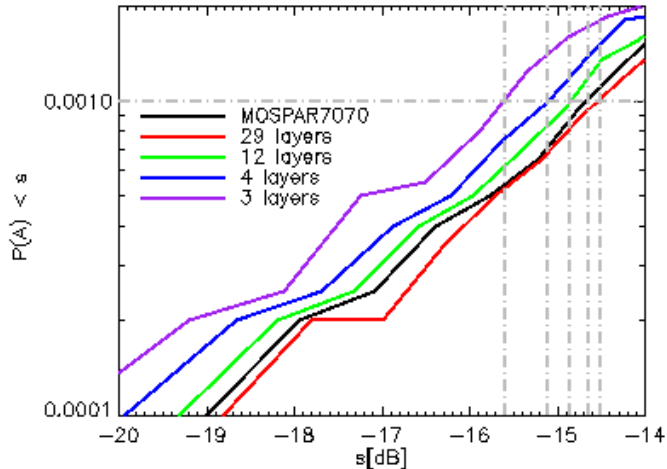


Fig. 3. Cumulated probability function of the uplink received optical power attenuation for the different profiles : MOSPAR7070 in black, 29 layers in red, 12 layers in green, 4 layers in blue, 3 layers in purple.

III. ATMOSPHERIC TURBULENCE PARAMETERS PREDICTION

In the previous subsection, we focused on the short term performance estimation. The aim of this section is to investigate, for a time horizon of the order of an hour or more, the temporal prediction of key atmospheric turbulence parameters, specifically the Fried parameter (r_0), the isoplanatic angle (θ_0), and the atmospheric coherence time (τ_0). These parameters exhibit high temporal variability, and accurate prediction is crucial for the optimal operation of optical communication systems. To achieve this, we explore the use of deep learning models, such as N-BEATS and N-HITS.

To construct a database, we rely on WRF (Weather Research Forecast) simulations. WRF is a numerical weather prediction model that provides valuable insights into the atmospheric conditions that affect turbulence parameters such as temperature vertical profiles, wind speed vertical profiles and more. C_n^2 profile estimation from WRF outputs has been performed using the model described by F. Quatresooz in [18]. To estimate the reliability of the results, we selected a location and a time period for which we had access to local integrated parameter measurements. Four temporal periods were selected, October, April, July and August of 2021 to cover different seasons. Simulations were done for the Teide observatory (28.30228, -16.51032) at altitude 2390 m where a differential image motion monitor (DIMM) measuring the Fried parameter has been installed by Miratlas. The instrument is positioned

on a 7 meter high tower to limit the sensitivity to the most intense ground phenomena.

r_0 was measured only during day time due to a failure of the night time instrument. However, since the systems dedicated to free space optics will have to cover all the turbulence conditions likely to be encountered, they are designed for demanding turbulence conditions, which almost always occur during the day. In this respect, the database supplied by Miratlas provides representative measurements, as it covers daytime conditions.

First step of validation of WRF data has been to look at the meteorological parameters on the ground level.

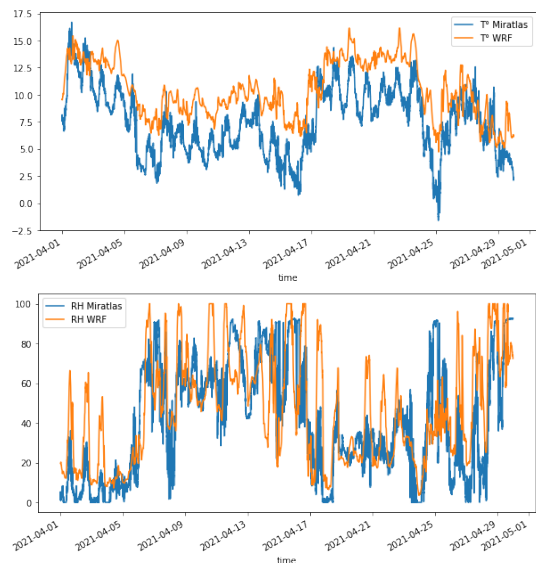


Fig. 4. Comparison of the temperature and humidity on the ground level obtained through WRF (orange) and measured through the local meteorological station (blue)

As we can see on Figure 4, the trend is well represented here through the month of April but similar comparisons are obtained for the other months. Nevertheless, a systematic error appears on the simulation of the ground layer temperature using WRF, this could be due either to the height of the first layer not being extremely accurate or due to the fact that the nature of the ground is not accounted for in our simulations.

The high frequency variation in temperature or relative humidity over short time scales is not accurately described, this is even more visible when comparing the simulated r_0 values in April as we did in Figure 5. WRF at best gives an average value of the Fried parameter over a couple of hours but does not translate the high frequency variability.

The reasons are numerous:

- WRF simulations are conducted on a grid with a large spatial resolution compared to the local variations in atmospheric parameters. This is particularly true for fine-scale processes such as optical turbulence parameters that have, close to the ground, an outer scale of a few metres.

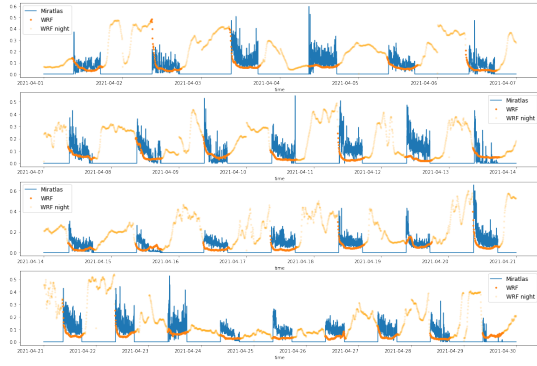


Fig. 5. Comparison of the r_0 obtained through WRF (orange) and measured through the local meteorological station (blue)

- WRF uses parametrisation schemes to simulate the processes at unresolved scales like turbulence and boundary layer interactions, which are the processes contributing to large-scale variability. Nonetheless, these parametrisation schemes are only statistical models.
- The region being simulated presents complex terrain and heterogeneous land, which leads to challenges in accurately representing local atmospheric conditions that cannot be solved using only WRF.
- The 5 minutes temporal resolution of WRF involves temporal averaging, which smooths out high-frequency variability, while the local measurement consists of the acquisition of a point every minute without any averaging being done.

Despite these intrinsic limitations WRF simulations are able to capture the larger-scale trends and patterns in the atmospheric data. They give us an idea of the evolution of each layer of the atmosphere for kilometres around the observation point.

These considerations led us to continue the prediction work on WRF data only, for exploratory purposes and with the aim of developing interesting models for forecasting over mid-term time periods. This was done using two newly-presented deep neural network temporal prediction model called N-BEATS and N-HITS and compared to the latest state of the art model from integrated parameters prediction ARIMA+VMD presented in [19]. The training process is always the same. Each month is separated into 2 times 15 days, the first being used as a training set for the models, and the second being used as validation set. It was determined that the prediction gives the best results for an input time series of the model of 5 to 7 days.

The best results were obtained with N-BEATS, while N-HITS is usually more suitable for long trends and requires a more complex parametrisation. Figures 6 shows two relevant examples of the kind of probabilistic prediction obtained using N-BEATS. For each of these cases, we have applied quantile regression with quantiles corresponding to a 95% confidence

interval.

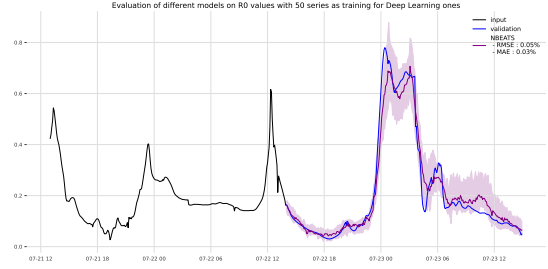
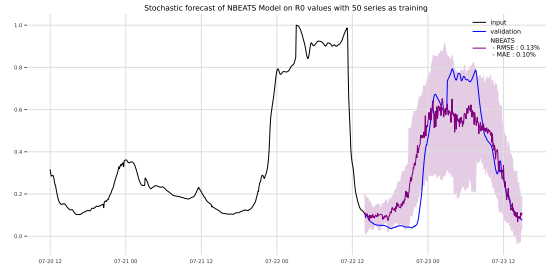


Fig. 6. Two examples of prediction of r_0 over one day using N-BEATS for July

The model visually gives impressive prediction but is still basic as it only uses moments from the past 7 days to predict the upcoming ones. This results in good trend prediction, but the model would not be able to anticipate unexpected variation due for example to high ground turbulence (sudden change in temperature or wind speed).

This was accounted for by implementing the use of past covariate to these models. Looking at correlations between the moment of interests and the meteorological data available in WRF simulations, we selected two covariates: temperature at a ground level and the ground Turbulent Kinetic Energy (TKE). Adding these measurements to the input of the model allows to learn the relationship between the past meteorological condition and the future moment, which improves the precision the predictions with metric scores decreasing by 5 to 15% depending on the case (lower is better). All metrics are visible in the next Table II.

As can be seen in Figure 7, adding the temperature as a past covariate, not only improves the prediction compared to the TKE only case, but also lowers significantly the precision interval of the prediction making it much more reliable.

From all scores presented in Table II, it is clear that the latest temporal prediction model NHITS does not behave better than the ARIMA based method in our case and the reasons remain unclear. It could be that the more complex architecture of NBEATS, even though it is slower, allows us to learn more complex patterns in the data, which can lead to better predictions. The ability of NHITS to capture long-term dependency much better than NBEATS is probably not as relevant in our case, since there is little long-term dependency in moments due to the nature of atmospheric phenomena.

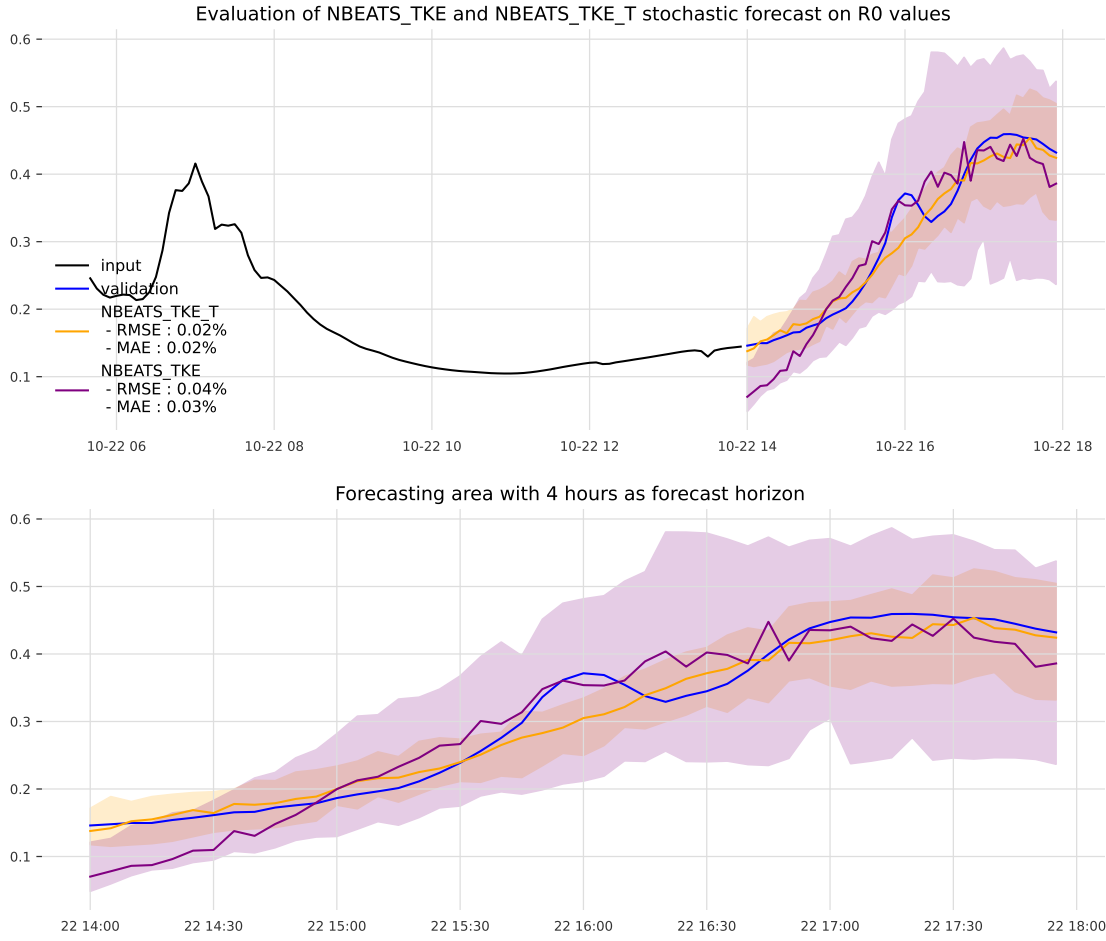


Fig. 7. Comparison of N-BEATS with TKE (purple) as a past covariate and with T° + TKE (yellow) as past covariates for a prediction of a few hours the 22nd of October.

TABLE II
PREDICTION SCORE FOR THE DIFFERENT MODELS AND DIFFERENT MOMENTS OF INTEREST. THE LEFT SCORE IS THE RMSE AND THE RIGHT ONE THE MAE

| Moments | r_0 | τ_0 | θ_0 |
|------------------|-------------|-------------|-------------|
| $ARIMA_{VMD}$ | 0.100/0.087 | 0.128/0.117 | 0.119/0.109 |
| $NHITS$ | 0.096/0.081 | 0.128/0.118 | 0.127/0.120 |
| $NBEATS$ | 0.071/0.061 | 0.075/0.068 | 0.083/0.076 |
| $NBEATS_{TKE}$ | 0.069/0.059 | 0.073/0.066 | 0.076/0.069 |
| $NBEATS_{TKE_T}$ | 0.061/0.049 | 0.070/0.063 | |

In spite of this, NBEATS outperforms the current state-of-the-art ARIMA + VMD model regardless of the moment considered. The prediction score can slightly be improved with the addition of the TKE as a past covariate and even further adding the temperature measured near the ground as well.

One key area of improvement lies in the incorporation of future covariates, such as meteorological forecasts from mesoscale models, to provide more forward-looking predictions. Additionally, composite models that combine local measurements and outputs from meteorological models like WRF could offer a comprehensive solution, capturing both trend predictions and high-frequency variability. Lastly, robust uncertainty estimation methods should be developed to provide reliable confidence measures for the composite predictions.

IV. EXPERIMENTAL PLAN

Reliable temporal characteristics of the received optical power are for instance mandatory to define appropriate impairments management strategies (interleavers, error correcting codes) and decline the corresponding constraints on the

space segment. Such models are emerging but they still lack experimental validations in relevant turbulence conditions.

A. Atmospheric transmission measurements

To validate the hypothesis on the transmission of the budget link, we will implement an atmospheric transmission assessment using MATISSE with Météo-France forecast data, 12 to 36 hours in advance. The MATISSE code is the DGA's reference code for modelling atmospheric radiative transfer on a global scale [20]. It provides atmospheric luminance and transmission over the entire optical spectrum. It has databases that can be used to fill in the input parameters: standard or climatological thermodynamic profiles, optical properties of aerosols and cloud types, reflectance of the ground, sea temperature, etc. This assessment will provide an initial estimate of the various contributors to transmission along the line of sight (molecular, cloud and aerosol transmission), with the temporal and spatial resolution of Météo-France forecasts, i.e. 2.5 km and 1 h respectively. Accuracy is limited to forecasts accuracy.

The FEELINGS ground station is equipped with ground-based measurement instruments to provide, after processing, precise characterisation on a local scale of parameters characteristic of atmospheric transmission: spatial distribution or integration along the line of sight, temporal evolution on a scale of a few minutes of microphysical and optical parameters. A visible all-sky camera and a ceilometer will be used to characterize clouds; a Sun Sky Lunar CIMEL photometer will be supplied to document aerosols. The data is usually displayed vertically from the instrument and at its wavelength. The use of a combination of sensors makes it possible to overcome the individual limitations of each sensor in order to access more parameters and improve the quality of the retrieval. The combination of a LiDAR (ideally bi- or multi-wavelengths), an All Sky visible camera, and day/night sunphotometer is an effective solution for describing the atmosphere. This description is based both on processes that combine the instruments and on complementary expertise on a case-by-case basis. Full automation of processing requires further development.

Feeding an atmospheric propagation code with local measurements of the atmosphere is the most interesting solution for meeting the need for local evaluation of transmission along the optical link and at the wavelength of this link. This approach benefits from the local description of the atmosphere by the measurements, which is decisive, and from the flexibility of the modelling in the choice of spectral bands and calculation scenarios. Since the parameters returned by local measurements are not always directly usable as input data for the code, they have to be translated into input parameters. This is the case for clouds and especially aerosols. As before, automatic access to code input parameters from measurements requires methodological developments. This is the next stage, which will provide in-depth knowledge of atmospheric transmission for the optical links with the FEELINGS ground station.

B. Validation of the link budget

In the specific case of geostationary ground-satellite links, it is necessary to validate in real conditions the assumptions made about the link budget especially for the largest contributors : geometrical losses (beam divergence and depointing), losses due to atmospheric turbulence and their correction by adaptive optics, losses inherent in the optical path and the impact of attenuation caused by the degraded transparency of the atmosphere (absorption, scattering).

The links are also an opportunity to demonstrate in real conditions the implementation of a laser amplifier that goes beyond the state of the art and whose optical characteristics are compatible with high-speed data transmission [2]. One of the main challenges of the use of such an amplifier is the implementation on the optical bench by sharing the optical path with a differential between the flux emitted at the pupil output and that received flux on the downlink telecom channel of 10 orders of magnitude.

C. Understanding the temporal and statistical characteristics of the received power

To ensure lossless transmission of information, data transmission reliability is based on the use of digital information processing (error correcting codes on interleaved data), the efficiency of which is highly dependent on the statistical and temporal properties of the propagation channel. A major challenge therefore lies in the ability to have reliable models of the statistical and temporal properties of the signal received at the broadband detection level. These properties are conditioned by the impact of atmospheric turbulence and its correction by AO, the performance of which is sensitive to the conditions of use.

To date, there is no AO system in operation on a telescope 24 hours a day and operating on an uplink. All the systems in operation on telescopes operate at night (in the case of astronomical applications or space observation) or on downlink optical links. The turbulence conditions to be addressed are also very poorly documented to date. To demonstrate the validity of the models in the range of conditions of use, it is necessary to characterise the properties of the high-frequency atmospheric channel at the same time as the data link, and to be able to reproduce the properties of the signal using models parameterised by the propagation conditions encountered.

V. CONCLUSION

Atmospheric turbulence will compromise optical feeder links availability unless appropriate strategies are put in place to mitigate and anticipate them. Properly assessing turbulence impact is critical to reach the availability requested from very high data rates optical links and finally provide connectivity as a service. Short term reliable performance estimation will be used to optimize AO based system operations, mid-term prediction will be necessary to ensure an uninterrupted handover. FEELINGS, ONERA's optical ground station demonstrator for optical feeder links will implement a real time performance assessment based on the use of a Monte Carlo model that

exploits an analytical description of AO residuals and spatial characteristics of turbulence induced complex amplitude impairments. This model is fed by systematic C_n^2 and wind profiles estimations. We focused here on the C_n^2 estimation process and put the emphasize on the influence of its key parameters. For a 10 s duration temporal horizon for data acquisition a 12 layers estimation result in a received optical power uncertainty of 0.2 dB. The estimation converges in less than 30 s keeping the computation cost within a typical stationary time of atmospheric turbulence. With respect to performance prediction, we demonstrated recently that an appropriately trained Artificial Intelligence (AI) exploiting Gaussian processes can provide reliable estimates of optical link availability while requiring a limited number of appropriately chosen integrated parameters. The possibility to predict such parameters offers the perspective to be able to predict link availability with an accuracy compatible with typically used link margins. We investigated here the possibility to exploit state of the art AI tools to predict atmospheric parameters within few hour. On WRF data the method provides very promising results with prediction errors smaller than 10 % within 1 hour timescale.

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