1 Modelling total solar irradiance from PMOD composite 2 using feed-forward neural networks

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7 Abstract

8 The variability of the solar activity dominates the variability of the earth's at-
9 mosphere, which affects human life and technology on earth. To understand
10 the effects of solar activity on earth's atmosphere different efforts are under-
11 way to model the variations of total solar irradiance (TSI) associated to the
12 variations of photometric sunspot index (PSI) and core to wing ratio of Mg
13 II index, for example, linear regression approach. In this study, feed-forward
14 neural networks (NNs) algorithm, which takes the non-linear relationship
15 between the dependent and independent variables, has been implemented to
16 model daily TSI using PSI and Mg II index. First, data between 1978-2008
17 have been used to train and validate NNs, through which the parameters
18 such as weights and biases are estimated. Therefore, NNs has been used to
19 predict TSI between the years 2008 to 2013 from test data. The output of
20 NNs have been compared with PMOD composite TSI and result has shown
21 good agreement. Linear correlation between NNs predicted TSI and PMOD
22 composite is found to be about 0.9307 for the years between 1978 to 2013.
23 This means that NNs predicted TSI from solar proxies explains about 86.6%
24 of the variance of TSI for solar cycle 21-24, and over 90% during solar cy-

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cle 23. Predicting TSI using NNs further strengthens the view that surface magnetism indeed plays a dominant role in modulating solar irradiance.

Keywords: Solar irradiance, sunspot, neural network

1. Introduction

Total solar irradiance (TSI), is the total power from the sun impinging on the Earth and its variation in solar radiative output clearly have the potential to affect our planet. This radiative output heats the land and ocean, maintains our atmosphere, generates clouds, and cycles water (Rottman, 2006). Studies conducted by astrophysical and meteorological communities have shown the fingerprint of solar activity on the Earth's climate (Beer et al., 2000; Gleisner & Thjill, 2003; Scafetta & West, 2006; Schrijver et al., 2011; Lean et al., 1995). Also researchers are working to understand the physical mechanism responsible for this influence (see,e.g., Ermolli et al., 2013; Krivova & Solanki, 2013, for a recent review).

For more than three and half decade solar irradiance has been monitored from space by different satellites and from these consecutive and partly overlapping time series measurements three TSI composites have been compiled. These are: the Active Radio Irradiance Monitor (Willson & Mordvinov, 2003), the Royal Meteorological Institute of Belgium (RMIB) (Dewitte et al., 2004) and the Physikalisch-Meteorologisches Observatorium Davos (PMOD) (Fröhlich, 2006). Each composite has their own calibration techniques and mathematical algorithms. They show certain differences, of which the most important regards the presence of an upward secular trend between the minima preceding cycles 22 (1986) and 23 (1996) (Krivova et al., 2011).

49 It is well known that following the 1978 satellite solar irradiance data, var-
 50 ious empirical and semi-empirical models have been developed to reconstruct
 51 total solar irradiance from solar activity. The models which assume that ir-
 52 radiance variations on a time scale longer than roughly a day are caused their
 53 changes in the surface distribution of different magnetic features have turned
 54 out to be most successful in explaining observed irradiance changes (Solanki
 55 et al., 2013). Authors like Fröhlich & Lean (2004); Balmaceda et al. (2007);
 56 Vaquero et al. (2006) used empirical TSI modelling to address the question of
 57 the extent to which variations in TSI can be explained using only variations
 58 due to magnetic features such as sunspots, faculae and network. Sunspots
 59 cause deficits in the irradiance, while faculae and network cause excesses.
 60 The fact that the TSI is on average higher near sunspot maximum implies
 61 that the influence of faculae and network is greater than that of sunspots
 62 (Fröhlich & Lean, 1998). Proxy-based models (see, Ashamari et al., 2015,
 63 for a recent review) try to answer the question: to what extent specific solar
 64 proxies, such as sunspot number, Mg II index, F10.7 radio flux, abundance
 65 of cosmogenic isotopes, spectral lines or specific wavelength bands in the ob-
 66 served solar spectra or solar intensitygrams, can be used to describe solar
 67 irradiance variability. This proxy-based empirical model is very successful in
 68 reproducing the observed TSI variations from 1978 to 2004, but it fails to
 69 explain the decrease observed since 2005 (Fröhlich, 2009). The advantage of
 70 employing radiances computed from the semi-empirical model atmospheres
 71 is that they allow computations of solar irradiance at different wavelength
 72 (i.e. spectral irradiance) (Yeo et al., 2014a,b). This is not straightforward
 73 with the regression models, since in this case the regression coefficients need

74 to be estimated from observations (Ermolli et al., 2013). Modelling of TSI
75 is of both scientific and practical interest.

76 Methods of artificial intelligence have provided tools which potentially
77 make the task of solar irradiance modelling and forecasting possible. For
78 instance, previous works (see, Mellit & Pavan, 2010; Alzahrani & Kimball,
79 2014; Faceira et al., 2015, for a detail review) showed that the feasibility of the
80 neural networks approach in modelling the non-linear relationship between
81 solar radiation and geographical and meteorological parameters. Results
82 of their study showed that neural networks allow estimating the values of
83 radiation with great precision in various regions of the world. However, in
84 this paper we concentrate on TSI modelling from PMD composite that was
85 compiled from different space-borne measurements using feed-forward neural
86 networks approach.

87 The main goal of this paper is to investigate whether the feed-forward
88 neural networks (NNs) model can explain the recently observed negative
89 trend in the TSI, or an additional component as proposed in Fröhlich (2009)
90 is needed. For this purpose, two most commonly used basic indices : the
91 photometric Sunspot Index (PSI) and Mg II index were used as a proxy data
92 for solar magnetic activity. As pointed out by Fröhlich & Lean (2004) the Mg
93 II index is treated into the long- and short-term components, $Mg II_{lt}$ and Mg
94 II_{st} , respectively. The long-term component was calculated by convolving the
95 Mg II index with an 81-day Full-Width Half-Maximum (FWHM) Gaussian
96 function. The difference between Mg II index and long-term component
97 represents the short-term component. Our investigation is carried out for
98 the time interval of 1978 to 2013, which represents nearly four solar cycles.

2. The measurement and analysis

2.1. The measurement

The input data have been taken from the solar indices that have impact on the TSI variations such as the daily PSI, and composite Mg II index. The daily PSI indicates the solar activity and describes the radiation deficit caused by the spots. Sunspots can be modelled from their area and position on the disk by using an appropriate contrast and its result is PSI, which is given by part per million (ppm) of TSI. Daily PSI has been compiled by Balmaceda et al. (2009) and is available at: http://www2.mps.mpg.de/projects/sunclimate/data/table4_v0613.txt. This data is available starting from 1874, however, PSI data after November 17, 1978 to 2013 has been considered for our study. The composite Mg II index from 1978 to 2013, which is available at <http://www.iup.uni-bremen.de/gome/gomemgii.html>, was used to estimate the effect of faculae and network on solar irradiance Variability. This Mg II index, which is the core-to-wing ratio of the irradiance in the core of the unresolved Mg II doublet at 280 nm to the nearby continuum irradiance and measures solar variability on both rotational and solar cycle time scales (Deland & Cebula, 1993). Thus, these indices are considered as an input parameter for TSI modelling by considering their short term as well as long term influences on solar activity. Total solar irradiance data version d41_62.1302 from PMOD/WRC, Davos, Switzerland, used as a target. Figure 1 shows daily values (black) and 191-day running means (red) and from top to bottom: the PMOD composite of the TSI, PSI, Mg II_{st} , and Mg II_{lt} from the year 1978-2013 respectively.

Figure 1: Daily values of the time series a) TSI (PMOD composite) b) photometric sunspot index (PSI) c) Mg II_{st} and d) Mg II_{lt} index. The period covers from November 17, 1978 up to October 31, 2013.

123 2.2. The analysis

124 Neural networks (NNs) are mathematical system which can be able to
 125 model the ability of biological neural networks by interconnecting many sim-
 126 ple neurons. The neuron accepts inputs from a single or multiple sources
 127 and produces an output by training process with a predetermined non-linear
 128 function. NNs are capable of directly correlating the time series of multi-
 129 ple input variables to the output variables through the interconnected nodes
 130 using trainable weights and bias signal (Hagan et al., 1995). NN is an im-
 131 portant tool for non-linear approximation when it is trained with sufficient
 132 historic data (Habarulema et al., 2007).

133 The two primary components of the NNs are the processing elements and
 134 their interconnections. Figure 2 shows a fully connected single hidden layer
 135 feed-forward NNs. As it is shown in the figure, there are three categories of
 136 layers in a neural network: input, hidden and output layers. Each layers is
 137 made up of several nodes, and layers are interconnected by sets of correlation
 138 weights. And also, each layer's computation is split into two components.
 139 First, a linear component, called the input function, computes the weighted
 140 sum of the layer's input values. For instance, in the case of seven hidden
 141 neuron j , we have:

$$net_j = \sum_{i=1}^3 w_{ji}x_i + b_j, \quad (1)$$

142 where x_i represents the input variables (such as PSI, Mg II_{lt}, and Mg II_{st}),
 143 w_{ij} is the weights of the neuron j , net_j is the linear combiner output due to
 144 the input signals, and b_j is the bias of the hidden neurons. Second, a non-
 145 linear component, called the activation function, transforms the weighted
 146 sum (net_j) into layer's final activation value. Different kinds of functions

Figure 2: Schematic of a single hidden layer, feed-forward neural network to reconstruct TSI.

are referenced in the literature, such as linear, sigmoid, hyperbolic tangent (Norgaard et al., 2000; Haykin, 1999; Demuth & Beale, 2000). In this work, we consider a hyperbolic tangent activation function (see Figure 2) for the neurons in the hidden layer. Hence, the value returned by the activation function of neuron j of the hidden layer is given by:

$$f(net_j) = 1 - \frac{2}{(\exp(2net_j) + 1)}. \quad (2)$$

Then, the outputs of all the hidden neurons are weighted and sent to the output layer, which contains a unique node n . It returns the prediction as:

$$TSI_{pre} = \sum_{j=1}^7 \hat{w}_{nj} f(net_j) + \hat{b}_j = \sum_{j=1}^7 \hat{w}_{nj} f\left(\sum_{i=1}^3 w_{ji} x_i + b_j\right) + \hat{b}_{nj}. \quad (3)$$

where TSI_{pre} is the predicted TSI of the output neuron, $\hat{w}_j$ is the weight of

the output of the j^{th} hidden neuron at the output neuron, and $\hat{b}_j$ represents the bias associated to the output neuron.

Learning occurs through the adjustment of the weights and node biases. The most common method used for adjustment is back-propagation. Back-propagation can train multilayer feed-forward networks with differentiable transfer functions to perform function approximation, pattern association, and pattern classification (Demuth & Beale, 2000). The term back-propagation refers to the process by which derivatives of network error, with respect to network weights and biases, can be computed.

The error at the output layer in the back-propagation NNs model propagates backward to the input layer through the hidden layer in the network to obtain the final desired output. This process can be used with a number of different optimization strategies. The detail analysis of back-propagation algorithm is given by Gong et al. (2012); Haykin (1999); Svozil et al. (1997); Rumelhart et al. (1986) and Bishop (1993). This means the desired behavior can be evaluated by the error function E , which is given by:

$$E = \frac{1}{2} \sum_{j=1} E_j^2 = \frac{1}{2} \sum_{j=1} (TSI_{meas}^j - TSI_{pre}^j)^2. \quad (4)$$

where TSI_{meas} and TSI_{pre} represent the target and predicted values of output neuron, respectively.

2.3. Neural network training and performance measures

Among the various NNs structures, we have used a basic structure known as a feed-forward neural network with Levenberg-Marquardt (LM) back-propagation algorithm. The LM algorithm was designed to approach second-order training speed without having to compute the Hessian matrix. This

178 method combines, in the same weight updating rule, both the gradient and
179 the Gauss-Newton approximation of the Hessian of the error function. This
180 makes it less complicated and memory demanding, that is why it is often
181 used in NNs training and was chosen also for the purpose of this study. A
182 more detailed description of LM algorithm can be found in Mellit & Pavan
183 (2010).

184 The network is feed-forward because the elements in one layer are only
185 connected to the elements in the next layer and the information moves for-
186 ward from one layer to another toward the output layer. At the training stage,
187 both the inputs and the desired output (TSI) are presented to the network.
188 Through learning algorithm the network produces its own output and tries
189 to minimize the discrepancies between its own output and the measured TSI.
190 After training and verification have been successfully completed, the model
191 weight and bias parameters can be saved for future application. We applied
192 batch training process, in which weights and biases are only updated after
193 all the inputs and targets are presented.

194 A well-known problem with NNs models like feed-forward is that they
195 can overfit the training data and not generalize well to new data outside the
196 training set (Srivastava et al., 2014; Soński, 2011; Demuth & Beale, 2000).
197 This can be prevented by using various methods like early stopping, pruning,
198 Bayesian regularization and weight decay to minimize the risk of over-fitting.
199 In the case of early stopping technique improvement of generalization of the
200 training can be achieved by dividing the available data into three subsets.
201 Here we follow the same procedure by dividing the data into training, vali-
202 dation and testing set. Data from November 17, 1978 to September 25, 2003

with 8151 observations are used for model building, and the next 1746 observations in September 26, 2003 and July 25, 2008 are used for the validation purpose. The out-of-sample period is from July 26, 2008 to October 31, 2013 and consists of the last 1746 data points which are used for testing. The model building data set is used to estimate model parameters and validation set is to check the performance of the network to determine the epoch at which training should be stopped to avoid over-fitting or over-training. The testing set is used to assess final overall performance of the NNs.

In order to achieve optimum NNs model, Root-Mean-Square Error (RMSE), correlation coefficient and the absolute error are used in the analysis. The RMSE is also known as the fit standard error and the standard error of the regression. It is an estimate of the standard deviation of the random component in the data, and is defined by:

$$RMSE = \sqrt{\frac{1}{N} \sum_{i=1}^N (TSI_{meas}^i - TSI_{pre}^i)^2}. \quad (5)$$

where N is the number of data points, TSI_{meas} is the measured data by using satellites, and TSI_{pre} is predicted by the model (Härdle & Simar, 2003). In addition to RMSE, the model efficiency R^2 and mean absolute error were used as an indicator of the goodness of fit in this study. The model efficiency can be measured by:

$$R^2 = 1 - \frac{\sum_{i=1}^N (TSI_{meas}^i - TSI_{pre}^i)^2}{\sum_{i=1}^N (TSI_{meas}^i - TSI_{mean})^2}. \quad (6)$$

The mean absolute error refers to Eq. 7 and can be expressed by

$$MAE = \frac{1}{N} \sum_{i=1}^N |TSI_{meas}^i - TSI_{pre}^i|. \quad (7)$$

222 3. Results and discussion

223 A number of training runs have been performed using different numbers
224 of hidden neurons, and the statistics of the model performance for training,
225 validation and testing set are summarized in Table 1. As shown in this table
226 the network with single hidden layer of 7 hidden neurons has achieved the best
227 performance. The computed correlation coefficient value (R) between the
228 NNs output and the PMOD composite reflects the accuracy of the training
229 process. It is known that NNs interpolate well within the in-sample data
230 than for the out-of-sample period, and therefore the network is expected
231 to reproduce the data set that was used to train it with relatively good
232 accuracy (Habarulema et al., 2007; Habarulema & McKinnell, 2012). For
233 this purpose, the generalisation capability of the considered feed-forward
234 NNs model is assessed in prediction out-of-sample daily TSI data from July
235 26, 2008 to October 31, 2013. For prediction (extrapolation) period the
236 computed RMSE and MAE were 0.1274 and 0.0823 Wm^{-2} respectively and
237 these results show that NN-predicted TSI values are very close to the testing
238 set. The achievement of the trained network depends not only on the input
239 parameters and the number of hidden neurons but also on the initial weights
240 and biases. Therefore, initial weights and biases for the training process are
241 set to be random values.

242 The temporal comparison of model prediction and PMOD composite dur-
243 ing training, validation and testing phases are given in Figure 3a from the
244 year 1978 to 2013. Figure 3b shows the residuals between PMOD composite
245 and NNs model output. This residual is almost flat in all considered cycles.
246 The bottom panel of Figure 3c shows the overall trend in the PMOD com-

Table 1: Results of NNs techniques for training, validation and testing data set.

No of hidden neuron	Training		Validation		Testing	
	RMSE (MAE)	R	RMSE(MAE)	R	RMSE(MAE)	R
	(Wm ⁻²)		(Wm ⁻²)		(Wm ⁻²)	
1	0.2301(0.1576)	0.9174	0.1190(0.0936)	0.9533	0.1421(0.1075)	0.9360
2	0.2203(0.1260)	0.9243	0.1482(0.1016)	0.9334	0.1467(0.1128)	0.9340
3	0.2270(0.1570)	0.9194	0.1178(0.0836)	0.9486	0.1439(0.1062)	0.9424
4	0.2178(0.1521)	0.9261	0.1375(0.0975)	0.9407	0.1467(0.1116)	0.9347
5	0.2237(0.1569)	0.9218	0.1459(0.0876)	0.9325	0.1331(0.0992)	0.9493
6	0.2215(0.1529)	0.9235	0.1389(0.1025)	0.9480	0.1439(0.1113)	0.9364
7	0.2271 (0.1586)	0.9200	0.1316 (0.0855)	0.9389	0.1274(0.0823)	0.9394
8	0.2387(0.1627)	0.9106	0.1251(0.0955)	0.9434	0.1542(0.1100)	0.9219
9	0.2420(0.1621)	0.9081	0.1267(0.1003)	0.9457	0.1512(0.1139)	0.9312
10	0.2261(0.1566)	0.9201	0.1620(0.0918)	0.9067	0.1376(0.1043)	0.9452
11	0.2292 (0.1567)	0.9178	0.1885(0.0968)	0.9448	0.1467(0.1079)	0.9301
12	0.2174(0.1521)	0.9264	0.1440(0.0947)	0.9340	0.1422(0.1073)	0.93861

posite is well replicated in Spectral And Total Irradiance REconstructions for the Satellite era (SATIRE-S) and NNs modelling approach. The SATIRE-S reconstruction is higher between 1984 and 1994 (see Yeo et al., 2014b, for details) while the NNs prediction between 1984 and 1994 slightly lower by about 0.2 and 0.3 Wm⁻² from PMOD composite.

To examine the linear association between the total solar irradiance for the training, validation and testing data and NNs model output, we present a scatter plot for each category in Figure 4. The green colored solid line represents the best fit linear regression line between between the NNs prediction and PMOD data sets. In each panel, the corresponding correlation coefficient R, and the linear equations are given. The right bottom panel of

Figure 3: a) NNs reconstruction of TSI (red, blue and magenta), and PMOD composite records (black). b) Difference between NNs predicted TSI, and PMOD composite. c) SATIRE-S (Yeo et al., 2014b) reconstruction of TSI, NNs prediction of TSI and PMOD composite records of TSI. All the time series were normalized to TIM at the 2008 solar cycle minimum (horizontal broken line) and smoothed with a 181-day moving average.

the figure shows the scatter plot of the daily TSI values for year 1978-2013
 predicted by feed-forward NNs method using data of PMOD composite times
 series, as a function of PSI and MgII index data. The result shows that the
 feed-forward NNs model was satisfactorily trained to determine the weight
 and bias parameters in the network so that the model output well match with
 the PMOD composite. This performance is achieved based on 11643 data
 points. The measured TSI and model prediction has a correlation coefficient
 of $R = 0.9307$, and this means that 86.6% the total variation of the TSI is

266 due to these solar proxies. This three component NNs model showed a better
 267 prediction than to the goodness-of-fit achieved by other empirical models of
 268 TSI which is done by Fröhlich & Lean (2004) using multiple linear regression
 269 analysis and their three component model was able to explain 78.6% of the
 270 variance of TSI. The prediction confirms the assumption that great part of
 271 the solar irradiance are due to the surface magnetism (sunspot, faculae and
 272 networks) on the solar cycle and secular time scales (Krivova et al., 2007;
 273 Solanki et al., 2005).

274 A detailed analysis of the composite time series is presented in Figure 5
 275 and we showed the results of NNs model to PMOD composite time series
 276 data for solar cycles 21, 22, 23 and 24 separately. The green dotted point
 277 indicates a 27-day running mean of the daily values of TSI obtained using the
 278 NNs model, while the dark line shows the 27-day running mean variation in
 279 the PMOD composite time series values. The goodness of fit of statistics for
 individual solar cycle including the number of data points is given in Table 2.

Table 2: Statistics of NNs model and PMOD composite time series data correlation, RMSE and regression coefficient for solar cycle 21, 22, 23, and 24.

Year	Data set	Solar Cycle	RMSE (Wm^{-2})	MAE (Wm^{-2})	R	R^2
1978-1986	2334	21(part)	0.2675	0.1917	0.8993	0.7273
1987-1996	3445	22	0.2218	0.1535	0.9219	0.8499
1997-2008	4277	23	0.1636	0.1105	0.9565	0.9149
2009-2013	1587	24 (part)	0.1324	0.0866	0.9327	0.8699

280

281 In our analysis a high correlation is found for solar cycle 23. Research findings

Figure 4: Comparison of the NNs prediction and targets for training, validation and testing data sets.

indicted that at the end of the declining phase for cycle 23 and the beginning of solar cycle 24, the sunspot area was comparatively smaller and Mg II index higher. Therefore, inter-cycle variation can be found between the indices and total solar irradiance (Fröhlich, 2009). The growth of sunspot area is believed to cause changes in the TSI (de Toma et al., 2001), but observations show that the strength of the TSI cycle did not change significantly, despite the decrease in sunspot activity in cycle 23 relative to cycle 22 (de Toma et al., 2004; Fröhlich, 2013). The reconstructed TSI from three component model (Fröhlich, 2009) by using multiple regression doesn't show the pattern of the measured TSI. However, the result of NNs model shows that the predicted TSI using magnetic feature data is well estimated and the pattern of the measured TSI explicitly shown for each solar cycle. The reason is that we

Figure 5: The 27-day running mean of the predicted total solar irradiance using NNs models based on PSI and Mg II index data for solar cycle 21, 22, 23, and 24 is shown by a green dotted line. The 27-day running mean of the observed TSI is shown by the black solid line.

294 have used a data driven approach called feed-forward NNs that learns from its
 295 error iteratively whereas traditional regression model represents only linear
 296 relationships between dependent and independent variables. This allows us
 297 to suggest the reason why we cannot explain the pattern of the measured
 298 TSI using the model of magnetic features may be due to the model (multiple
 299 linear regression) itself. Multiple linear regression model depends on the time
 300 resolution and choice of the training period and this is the main shortcoming
 301 of this model (see Usoskin, 2013, for a recent review). The pattern of the
 302 reconstructed output (TSI) of the model indicates that the solar proxy (PSI
 303 and Mg II index) is greatly account for the variance of TSI.

304 In order to show more comparison, we plot a daily value of total solar
 305 irradiance data with NNs model for solar cycle 23 (Figure 6). We consider
 306 the daily variation in the modelled and measured total solar irradiance at
 307 low solar activity, rising solar activity, high solar activity, and declining solar
 308 activity. The dark solid line is for the TSI data from PMOD composite
 309 times series and the dotted (green) are for modeled values . We can see
 310 from Figure 6 that the NNs model and the measurement agree well for the
 considered solar cycle 23 periods.

Figure 6: The daily variation in the modelled and measured total solar irradiance at a) low solar activity, b) rising solar activity, c) high solar activity, and d) declining solar activity during cycle 23. The solid line is for the TSI data from PMOD composite times series and the dotted (green) are for modelled values.

311

312 4. Conclusions and future works

313 In this paper, we present the prediction of daily TSI from solar proxies
 314 (PSI, Mg II_{st} and Mg II_{lt}) by using NNs modelling technique. A single layer
 315 feed-forward approach with LM back-propagation algorithm implemented to
 316 determine weights and biases in the training. Although the parameters of
 317 the model were chosen by experimentation.

318 The prediction capability of the NNs was evaluated by the statistics of the
 319 root mean square error, mean absolute error and the correlation coefficient
 320 between PMOD composite and the predicted TSI. A comparison between the
 321 PMOD composite and the one predicted using the developed feed-forward
 322 network prediction shows a good performance for the out-of-sample data and
 323 the their correlation coefficient is about 0.9394. Although, we found a good
 324 agreement between PMOD composite and the predicted TSI (R=0.9307 over
 325 the span of the record, 1978 to 2013). Therefore, this model has able to
 326 explain 86.6% of the variance of TSI for the entire period. The dynamic
 327 nonlinear trend in the PMOD composite is well reproduced in all solar cycles
 328 (21-24) except between 1984 and 1994 where the prediction is lower by about
 329 0.2 and 0.3 Wm⁻² from PMOD composite. This is a substantial improvement
 330 to the traditional methods (Fröhlich & Lean, 2004) which were able to explain
 331 only 78.6% of TSI variations. This improvement is archived due to ability of
 332 NNs to represent both linear and non-linear relationships, as compared with
 333 traditional regression models which work for linear relationships.

334 The implication of the close correlation between PMOD composite and
 335 the predicted TSI is that the assumption behind the model is good and the
 336 surface magnetic field causes the irradiance variations on the time scales of

337 days up to the solar cycle. Also we can conclude that using PSI, Mg II_{lt}
 338 and Mg II_{st} as proxy to reproduce the solar irradiance by means of NNs
 339 model is useful to understand the temporal variations of the emitted energy
 340 at all wavelengths. Our future research work is to extend TSI prediction for
 341 epoches before irradiance observation began.

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 346 PMOD/WRC, Davos, Switzerland, PSI data from IMPRS and composite Mg
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