

*Original Research Paper

Technoeconomic Projections with Artificial Neural Networks Using an Ensemble of Sparsely-sampled Bootstrapped Data

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ABSTRACT

Aims: The present study refers to developing an artificial neural network (ANN) that can be designed exclusively for *ex ante* forecasting in technoeconomic contexts using an ensemble set of sparse and insufficient sampled-data availed *ex post*.

Study design: In general, availability of sampled-data sets in technoeconomic structures would largely be limited in number due to sparse-sampling; and as such, they are mostly inadequate for robust training of an ANN so as to make realistic inferences subsequently in the prediction phase. Hence a sparsity recovery strategy is advocated via statistical bootstrapping to enhance the inadequate sampled-data space for use in the test ANN. That is, the concept of applying statistical bootstrapping technique (on scarcely available, limited set of sampled-data) is invoked so as to obtain an enhanced number of data sets facilitating robust training of the test ANN.

Place and Duration of Study: The studies were conducted (2012-2013) at: Department of Computer and Electrical Engineering and Computer Science, College of Engineering & Computer Science, Florida Atlantic University, Boca Raton, Florida 33431, USA

Methodology: The study governs technoeconomic *ex ante* projections pertinent to a wind-power generation business complex elucidated *via* ANN-based forecasting. Relevant test ANN is designed to accommodate training with an ensemble of sampled set available *ex post* but, in limited numbers. The associated scarcity is recovered by artificially enhancing the data space to an adequate extent *via* bootstrapping techniques. Further, the test ANN designed corresponds to a multilayer perceptron (MLP) supporting backpropagation of the perceived error at the output with respect to a supervisory value. It accommodates the bootstrapped data space at its input relevant to technoeconomic details on a practical wind-power system performance reported in the literature. The training and prediction exercises on the test ANN corresponds to elucidating output predictions optimally in the context of the

technoeconomics framework of the power generation considered.

Results: Using the test ANN trained with bootstrap-enhanced, scarcity-recovered sparse data on wind-power generation statistics and associated plant economics, reliable inference (in the prediction phase) is achieved on the system performance. That is, the ANN output obtained depicts forecast projections on the productivity of electric power generation in the *ex ante* regime. Simulation studies thereof and results obtained demonstrate the efficacy of the method proposed, bootstrapping algorithm developed and the use of MLP in the technoeconomic contexts.

Keywords: *Technoeconomic Forecasting, Artificial Neural Network, Sampled-data, Bootstrapping, Scarcity Recovery, Wind-turbine Power Generation*

1. INTRODUCTION

A technoeconomic concern of modern time is to robustly assess the details pertinent to futuristic performance of the underlying business framework at micro- and/or macro-levels. Typically in technoeconomic contexts, projections on anticipated outcomes are enabled on the basis of statistically acquired details in the past and this *ex post* profile is judiciously extended to foresee the *ex ante* forecasting useful in decision-making efforts of the underlying business. Such forecast projections based on extending the *ex post* details normally rely on models and tools like time-series analyses, growth models, artificial intelligence, artificial neural networks (ANNs) etc. [1] [2]. In all such efforts, it is attempted that the outcomes projected and forecast made are rendered fairly robust and reliable consistent with observed details *ex ante*. Such assurance is however feasible, only if the *ex post* data adopted and applied on the models or tools are available to an adequate extent so that the stochastic features of the epochs of the past are projected effectively into the *ex ante* domain and are reliably tracked. However, it is not uncommon in practice that, mostly available prior data for use in aforesaid forecasting efforts on business performance evaluations are limited in number and sparsely indicated with details inadequately described. Such insufficient and scarce set of information would however, hamper making realistic and robust forecast inferences say, for example using the ANN strategy or otherwise.

Therefore, deducing forecasts even with inadequately captured *ex post* data is sought and emphasized in the present study. A relevant suite is proposed thereof to apply models and tools that conform to an ANN-based approach. Hence, by duly considering the inadequacy or scarcity of available (sampled) data, the data space is first (artificially) enhanced *via* the so-called statistical bootstrapping technique. Then, the test ANN is subjected to training with scarcity-recovered details (availed through post-bootstrapping exercise) and rendered thereof to yield a prediction performance on the output to a reliable extent.

Thus, the scope of the present study is to address the notions of technoeconomic forecasting using the proposed method using ANN. Relevantly, the consequences of applying inadequate ensemble of sample data as the ANN input (during training phase) is analyzed; and, the need to enhance the sampled data space, that is, exercising a scarcity recovery procedure so as to improve the ANN performance toward robust output predictions is indicated. Hence, a statistical bootstrapping algorithm is developed *vis-à-vis* scarcity removal in the sampled-data space availed *ex post* in typical technoeconomic contexts. The trained test ANN is then used for subsequent prediction exercise to obtain meaningful forecasts in the *ex ante* regime. The test ANN designed is based on a multilayer perceptron (MLP) architecture using backpropagation (BP) of the error schedule [3].

The (limited) sampled-data set considered here refers to a practical technoeconomic context of wind-turbine based power generation complex [4-6]; however, without any loss of generality, the methodology outlined can assess the technoeconomic performance of similar business structures. Performance prediction here implies elucidating optimally the underlying futuristic predictions (forecast projections) on the anticipated productivity across the *ex ante* regime. Simulation studies presented here are illustrative of practical implementation of the projected objective and hence, the studies performed are presented in sections as listed below:

- (i) In Section 2, the technoeconomic aspects of robustly assessing the futuristic prospects of the underlying business are outlined and the need for a reliable forecasting technique is indicated
- (ii) Suggested in Section 3 is a method toward such forecasting efforts via an ANN; and, the required architectural aspect of such an ANN is studied *vis-à-vis* the *pros* and *cons* of applying inadequate ensemble of data exercised as ANN input during the training phase. Corresponding reliability issues on the outcome in the prediction phase of the ANN operation are also analyzed
- (iii) The question of statistically enhancing the (inadequate) sampled-data space using the technique of bootstrapping is described in Section 4 and a relevant computational scheme on scarcity removal is outlined *via* a pseudocode
- (iv) An exemplary technoeconomic framework is identified in Section 5 wherein a limited extent of sampled data set is gathered pertinent to a practical context of wind-power generation complex [4]. Relevant sampled-data acquired is concerned with the information gathered from an ensemble of power generation *versus* wind-speed/direction details over a period of time-frame. This data set is designated as the *ex post* regime pertinent to a certain wind-speed and direction conditions
- (v) Designing an appropriate, bootstrapped-data based test ANN (abbreviated as BSD-ANN) for forecast purposes [7-13] is described in Section 6
- (vi) The training schedule and prediction performance of the BSD-ANN are addressed in Section 7. That is, the performance of the trained ANN in yielding output that conforms to *ex ante* predictions (and forecasts) on the technoeconomics of power generation *versus* wind-speed/direction parameters is evaluated in the prediction phase. Relevant simulation experiments are described and the results are presented with appropriate discussions
- (vii) Lastly, in Section 8, as a closure the efforts addressed in this study are summarized.

2. TECHNOECONOMIC BUSINESS AMBIENT AND RELIABLE FORECASTING

In economics sense, forecasting refers to a strategy of prediction depicting a “statement concerning unknown, in particular future, events”. So, any technoeconomic forecasting of interest would refer to the “best estimate” of futuristic projections of a (technoeconomic) entity with reference to its growth or decline as a function of time [1][2]. Alternatively, the performance projections can also be specified in terms of forecast values versus a performance variable of the underlying technoeconomics (instead of time). In practice, the techniques of forecasting rely on the database of the associated business variables, technological parameters, customer economics, company policies etc. depicting a set of prior knowledge in an *ex post* time-frame of the past. Mostly, such forecasting efforts include traditional suites of regression methods based on statistical concepts and heuristic modeling that apply to the database in question. Relevant forecasting theories pursued refer to interpreting the regression coefficients of the trend-curves of the variables established as a function of time. That is, an extrapolation of existing data *via* simple curve-fitting (regression) is done as a function of time in order to get a “forecast’ value. However, in order to reflect

the conjectural or stochastic aspects of technoeconomic details in the projected forecast curves, more involved versions of forecasting techniques have been indicated in the literature [1][2]. One such method refers to training an artificial neural network (ANN) with an ensemble of data known *a priori* and using the trained network, an output is sought in a prediction phase when subjected to an input of unknown data set. Relevant (converged) output observed is then analyzed to infer forecast details on a *posteriori* basis pertinent to the data space [7-13].

As indicated earlier, the forecast projections based *ex post* data largely rely on models and tools like time-series analyses, growth models, artificial intelligence, etc. [1][2]. In all such efforts it is implicit that the *ex post* data adopted and applied in the models are consistently adequate in representing the stochastic features of the epochs *ex post* as well as they reliably track such feature details forward in the projected *ex ante* domain at least to an extent within a cone-of-forecast as observed by Neelakanta and Yassin in [2].

Thus, the dogmatic aspect of forecasting in depicting the unknowns in future events on the basis of the known history of the past learned requires, (i) a comprehensive data set concerning the past (that is, the *ex post* details); (ii) ability of the forecasting tool to “learn” the features of the *ex post* epochs and (iii) the forecast engine judiciously track these features reliably at least within a pair of upper- and lower-bounds. Making of such a forecast inference engine is the motivated inquest of this study, which proposes the ANN pursuit as a compatible strategy as described below. Specifically, the ANN method described here allows inadequate sampled-data space of the past in the pursuit of futuristic forecast details; and, as mentioned before, the data suite considered is relevant to a technoeconomic base and statistical bootstrapping is prescribed for scarcity removal and to augment the extent of inadequate data samples.

3. ANN-BASED PURSUITS IN FORECASTING EFFORTS

Artificial neural networks refer to a class of models inspired by and “made in the image of biological nervous system” [3]. The architecture of an ANN in general is made of a set of interconnected computing elements called neurons (units). The network can be designed with an input layer having a prescribed number of input units and an output layer with a single output unit. In between, a set of hidden layers can be included with a designated number of neurons. The interconnections are synaptic links that connect to the inputs, output, or hidden neurons as illustrated in Fig. 1. A linear combiner is used to sum the output of the hidden layer so as to produce a single value (z_i) corresponding to the inputs addressed. That is, z_i implicitly denotes the weighted sum of all the inputs. It represents an activation signal and passed through a (sigmoidal) activation to produce a squashed output value (O_i), which can be compared against a teacher value (T_i) to yield an error (ϵ_i).

In general, there are several possible versions of ANN, but adopted in the present study is a particular type known as multilayer perceptron (MLP) shown in Fig.1. It depicts a feed-forward, multilayer architecture, which uses the so-called backpropagation (BP) algorithm in successive iterations of input training set in order to minimize the output error with respect to a supervisory (teacher) value [3] [14-18].

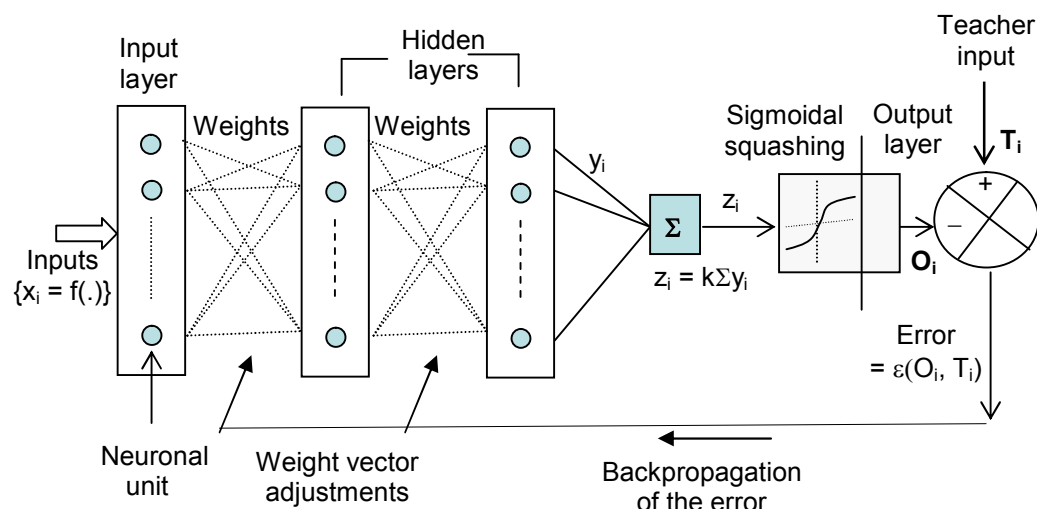


Fig. 1 The test ANN with MLP architecture

The MLP has the ability to “learn” complex relationships between input and output patterns. The inputs to the networks correspond to certain data being fed forward; and, this feed-forward exercise enables the network to get “trained” or made to learn (or gain knowledge) on the data passed through in repeated ensembles, each having a stochastic dispersion with respect to the objective functional value. The learning process also involves a supervisory effort. That is, for a given input addressed, the squashed output obtained is compared against a teacher value (denoting the desired convergence or objective function) and the resulting error is backpropagated iteratively so that, the network converges to yield almost a zero-error implying that its connecting synapses are duly weighted to hold the trained data pattern as a memory set. The training of the ANN is repeated multiple times with an ensemble of input data-sets, so that the network converges robustly. Subsequent to training, suppose a new input set (each having distinct stochastic features as mentioned earlier) is addressed. Then the network converges to the input received and concurrently the output error is seen minimized. That is, the network output designates the closeness of the new input set to the trained pattern.

The test MLP (Fig. 1) adopted in the present study has a simple architecture with only one hidden layer and both input and hidden layers consist of ten neurons each. Further, it has a single output node wherein the output is compared against a prescribed teacher value. Any resulting error is sensed and applied *via* backpropagation efforts that follow the suite of an algorithm that changes or adjusts the weights of the neural network iteratively. That is, a gradient-vector of the error surface is calculated and this vector follows the direction of steepest descent at each neural node in the backpropagation, so that the error is iteratively reduced seeking eventually the global minimum of the error trough.

In realizing ANN architectures such as MLP toward robust prediction performance, it is necessary that the test network should be trained adequately with sufficient extent of input data. In other words, for any meaningful classification of a given set of data *via* ANN method, the training of the ANN should be exercised with several iterations of input data set and each set is exhaustively defined. Then, the network will be robust in identifying and classifying a given set of new data freshly addressed on its input.

Most often the availability of ANN training data set will rather be restricted in numbers. More so, any such data set may not be of continuous to yield the full details across the sampled values of the data. Largely such data acquired in real-world context may correspond only to fragmented sampled details and as such, the data would contain only a partial information insufficient for robust training of the ANN. Essentially neural networks are data-driven, self-adaptive units, which can adjust themselves to a data without any explicit specification of the underlying model function. That is, ANN tends to represent the universe of approximation of any function with arbitrary extent of accuracy. Here, the accuracy refers to classifying a set of data of its closeness to a known class. In this sense, neural networks are estimator of an outcome based on posterior probability [14]. The question of accuracy on classification however, depends on two major considerations: (i) The complexity of the architecture and (ii) the extensiveness of the training input data set. Normally, the architecture is conceived with minimal extent of computational burden and time taken by the network toward convergence. Having designed an ANN based on reduced complexity, its performance in the prediction phase is decided by the extent of input training data on the learning patterns. In general sense, it is often assumed that the network is trained with sufficiently exhaustive set of input data. But, in reality as said earlier, the available data, in a particular context could only be sparse. Further, the functional dependence of the data is largely specified only as discrete sampled entity. Therefore pertinent to the scope of present study, in order to make the test ANN design compatible to handle limited data set and still offer acceptable performance in the prediction phase, the following considerations and queries are posed as regard to a given an ANN architecture, such as the MLP:

- How best can the ANN be trained with a sparsely-indicated sampled data set?
- How can the given sample-data population be enhanced or sparsity recovered so as to improve the confidence level of ANN prediction?
- How can a multiple set of a data be created artificially, when only an assorted and limited set of random samples are available?

Thus, in order to meet the context of a limited sample population for use as ANN inputs, an appropriate scheme of ANN training methodology has to be formulated. It should enable an optimal prediction model and a reliable network performance even under the conditions of source data being sparse. Relevant considerations are discussed in the following section.

4. APPLYING BOOTSTRAPPED DATA FOR ANN TRAINING

In the event of available data set being inadequate for robust ANN training, indicated in [19] is a method to build an ANN model with fairly accurate and reliable estimation performance. Hence advocated is a method of resampling based on the so-called statistical bootstrap method introduced by Efron in 1979 [20]. This method of bootstrapping became a popular statistical strategy in constructing more samples from a given sample set. When it is required to expand the realization of a statistical distribution of an inadequate variable set, creating a set of new bootstrap samples (of the variable) can provide a better understanding of the average and variability of the original, sparsely-known distribution of the statistical process. Bootstrap method in ANN modeling processes has been applied in the past to estimate the generalization error of an ANN; and, such ANNs are known as bootstrapped ANN where, each bootstrap sample is used to exercise the underlying ANN effort in the training phase. The relationship between model inputs and model outputs is approximately elucidated in such ANN strategies. Bootstrapped ANN models have been used in a variety of applications, including experimental data-processing, prediction of foreign exchange rates, predicting curls in paper-making modeling of an airfoil.

253 The basic heuristics of bootstrap method and its use in ANNs is as follows: Assume a small
 254 sample-set $\{(x_1, y_1), (x_2, y_2), \dots, (x_n, y_n)\}$ where x_i is the i^{th} input vector, depicting certain
 255 independent observations in a study and y_i denotes the corresponding dependent outcome
 256 variable; further, the observation pair (x_i, y_i) is independent and identically-distributed
 257 pertinent to an unknown/sparsely-known distribution, $F_{X,Y}$. A bootstrap approach can be
 258 invoked to replace this unknown/ sparsely-known distribution $F_{X,Y}$ by a new, empirical
 259 distribution $F^*_{X,Y}$ with a probabilistic density on (x_i, y_i) . That is, instead of generating new
 260 samples from the unknown distribution $F_{X,Y}$, a set of bootstrap samples are created by
 261 sampling with replacement of the empirical distribution, $F^*_{X,Y}$ with a probability density $1/n$ on
 262 each pair (x_i, y_i) . Thus, bootstrapping involves “a sample substituted with a replacement”.
 263 Because of the replacement process, each bootstrap sample may include multiple copies of
 264 some observations and no copies of other observations from the original set. The total
 265 number of bootstrap samples, B considered in practice, may range usually from 50 to 200;
 266 and, the set of B bootstrap samples can be expressed as $\{(x_1, y_1)_b, (x_2, y_2)_b, \dots, (x_n, y_n)_b\}$, with
 267 $b = 1, 2, \dots, B$.

268
 269 Given a sparsely sampled data-set, an ensemble of B bootstrapped data-sets can be
 270 constructed and used to train an ANN, B times; and, those observation pairs that are not
 271 included in the bootstrap sample-set can be used as a validation set to evaluate the
 272 performance of the trained ANN. Hence, the average performance of ANNs on their
 273 corresponding validation sets can be adopted as an estimate of the generalization error of
 274 the ANN models developed. Thus bootstrapping of sampled data and its application in ANNs
 275 are relevant to the state of sparse details being available. The level of sparsity specifies the
 276 extent to which one can discard the associated (small) coefficients without much conceptual
 277 loss. More generally, sparsity is a fundamental modeling tool that permits efficiently accurate
 278 statistical estimation and classification.

279
 280 For successful and robust application of bootstrapped ANN (BSD-ANN) conceived to
 281 support under sampled data environment, the following considerations can be identified:

- 282
- 283 ▪ Type of sampling: Uniform (equally-spaced) or non-uniform (randomly spaced)
- 284 sample space [21][22]
- 285 ▪ Sampling rate: Whether Nyquist-Shannon criterion on sampling is observed. (The
- 286 Nyquist-Shannon sampling theorem specifies an upper-bound on the sampling
- 287 interval (ΔT) of a discretized signal (sampled data) in time-domain such that the
- 288 sample contains all the available frequency information from the signal. The entity
- 289 ΔT is known as Nyquist interval. In short, the Nyquist-Shannon criterion stipulates
- 290 that for a lossless capture of information, the sampling should be at least twice faster
- 291 than the largest frequency content of the signal
- 292 ▪ Information recovery by a test ANN: Given a single set of sampled data satisfying
- 293 the Nyquist-Shannon sampling theorem, the problem is to derive an ensemble (B) of
- 294 sampled-data sets (from the given single set) required to train the test ANN.
- 295 Relevant construction of B ensemble sets should conform to asymptotically linear
- 296 multiples of sample-sets being necessary and sufficient to train the test ANN
- 297 adequately enough *vis-à-vis* the information recovery is robust in the prediction
- 298 phase
- 299 ▪ Bootstrapping constrained by Whittaker [23]–Shannon [24] criterion: Given a sample
- 300 set satisfying Nyquist interval ΔT , it can be stated that in the vicinity of this sampling
- 301 interval, the data points in the probability density function (PDF) are minimally
- 302 correlated; and as such, when bootstrapping is exercised to create an ensemble of
- 303 B new sampled data-sets, those data-sets would conserve the minimal correlation at
- 304 each bootstrap value so as to preserve the underlying information in the data
- 305 structure of the original, sampled data-set adopted for bootstrapping.

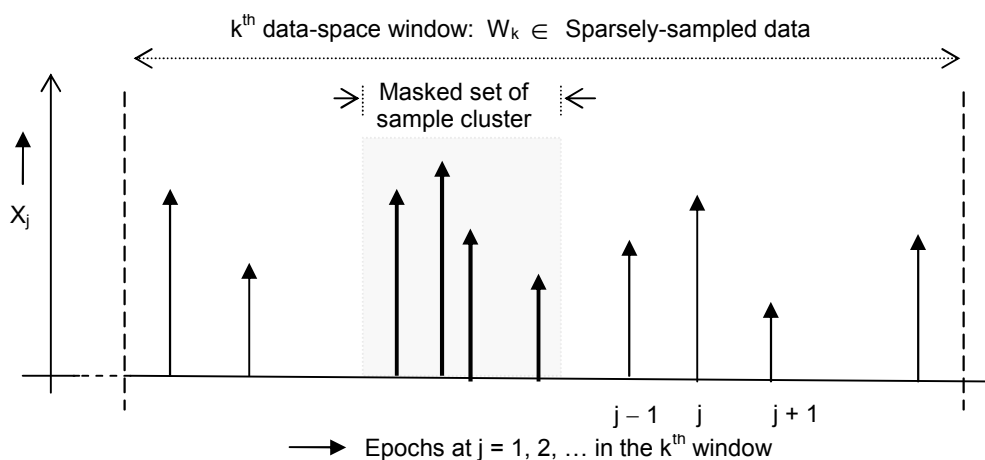
306
307 The question of statistically enhancing the (inadequate) sampled-data space using the
308 technique of bootstrapping is described below in terms of a relevant computational algorithm
309 outlined *via* a pseudocode.

310
311 **Pseudocode: Construction of bootstrapped samples**

312
313 **Initialize**

314 **Input**
315 → Sparsely-sampled data space of the set $X: \{x_j\}_{j=1, 2, \dots}$ with distribution F_X
316 ← Identify the k^{th} window of the data space wherein the bootstrapping is to
317 be done
318 ← List epochs of the samples at $j = 1, 2, \dots$ and note their values at each
319 epochs at locations (j) across the k^{th} window of the data space
320

321 **%% Illustrative example:**



322
323
324
325 **Fig. 2 Illustration of clustered and non-clustered parts of the epochs denoting**
326 **sparsely sampled data set in the k^{th} window**
327

328 **Perform**
329 → Segregation of clustered sample
330
331 ← Filter out/mask the clustered sample subspace as illustrated in Fig.2
332 ← Masked subspaces with clustered (closely-packed) will be excluded for
333 bootstrapping

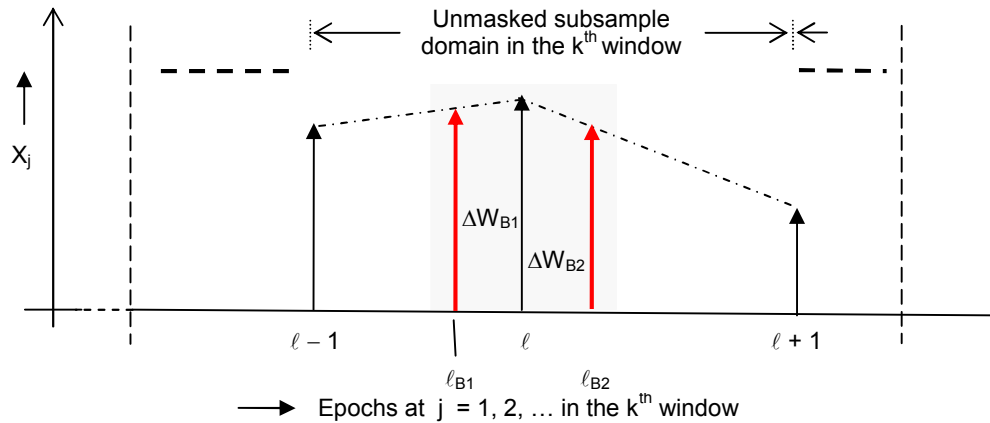
334 **Identify**
335 → Candidate samples/epochs in the unmasked, non-clustered sample space:
336 Step I

337
338 ← These samples, $\{X_i\}$ are subjected to bootstrapping

339 **Perform**
340 → Bootstrapping: A method of enhancing the number of samples/epochs
341 artificially at the candidate samples/epochs identified in the unmasked, non-
342 clustered sample space of Step I: $\{X_i\}$
343

- 344 ← These samples can be subjected to bootstrapping as follows:
 345 ← Track the slope of a candidate sample/epoch X_ℓ at the location ℓ across
 346 its neighbors $X_{\ell-1}$ and $X_{\ell+1}$ at locations $(\ell - 1)$ and $(\ell + 1)$ respectively.

347
 348
 349 %% Illustrative example:
 350



351
 352 **Fig. 3 Illustration of constructing new samples in the unmasked subsample domain in**
 353 **the k^{th} window**

- 354
 355
 356 **Go to**
 357 → Step II: Bootstrapping procedure *via* bilateral slope tracking
 358
 359 ← Here new samples/epoch are constructed *via* bootstrapping as follows:
 360
 361 ← With reference to a candidate sample/epoch X_ℓ at the location ℓ
 362 and its neighbors X_ℓ and X_ℓ placed at $(\ell - 1)$ and $(\ell + 1)$
 363 respectively, two fresh epochs are constructed bilaterally as
 364 illustrated at ℓ_{B1} and ℓ_{B2}
 365 ← The values, $(X_j \text{ at } j = \ell_{B1})$ and $(X_j \text{ at } j = \ell_{B2})$ are decided by the slopes
 366 across the candidate sample and its nearest neighbors
 367 ← The locations of these samples/epochs namely, at $j = \ell_{B1}$ and $j = \ell_{B2}$
 368 are set by the sample-intervals ΔW_{B1} and ΔW_{B2} respectively
 369 juxtapositioned with reference to the candidate sample/epoch at $j = \ell$
 370 ← The sample-intervals ΔW_{B1} and ΔW_{B2} are constrained by the norms
 371 of the sampling theorem and Nyquist sampling rate
 372 ← $(X_j \text{ at } j = \ell_{B1})$ and $(X_j \text{ at } j = \ell_{B2})$ are bootstrapped samples obtained
 373 with reference to the candidate sample/epoch at $j = \ell$ having
 374 bilateral offsets ΔW_{B1} and ΔW_{B2} (that are less than or equal to
 375 Nyquist sampling interval.)
 376
 377 **Go to**
 378 → Step III: Enhancing the population in the chosen window of the sampled
 379 data space *via* bootstrapping procedure of Step II

- 380 ← Step II can be repeated (to a desired extent) in order to construct new
- 381 samples/epochs, pursuing bootstrapping exercised at other candidate-
- 382 sites in the unmasked subsample domain in the k^{th} window
- 383 ← Thus, all the windows of interest can be subjected to population
- 384 enhancement on the sampled data as required

385 End

388 5. FORECASTING WITH SPARSELY-SAMPLED TECHNOECONOMIC DATA 389 SPACE

390
391 To illustrate the efficacy and practical applicability of the proposed strategy, the
392 technoeconomic data considered here for forecast applications refers to the performance
393 details of a power-grid pertinent to electric energy accessed from wind-propelled electric
394 generators. Relevant details on the exemplar technoeconomic system chosen are as
395 follows:

396
397 Abundant wind resources on the earth lend themselves as viable candidates of extensive
398 energy source conceived *via* electric generators using wind-turbines as prime-movers.
399 Hence, landscapes of wind-turbine farms are emerging profusely to cope with global
400 demand for clean energy; and, the footprints of such farms are mushrooming and scattered
401 all around the world at different geographical locales under diverse climatic conditions. As
402 such, it can be expected that depending on location and season, the wind turbines may face
403 significant variations in wind-speed and direction over different times of the year.
404 Correspondingly, it can be concurrently expected that the electric power generated would
405 fluctuate extensively with appreciable magnitude. Further, such fluctuations could largely be
406 continuous, partly intermittent and mostly stochastic. In any case, it is obvious that the
407 electric-power tapped from a wind-farm should be judiciously imparted to the power-grid
408 despite of the associated stochastics so that the load-sharing is accomplished smartly
409 across different energy sources supported on the grid *in situ* and evenly distributed. This will
410 assure a productive technoeconomic ambient on the scenario in question.

411 In order to facilitate productive technoeconomics to achieve logical and intelligent load-
412 sharing, it is necessary to know *a priori* the extent of power output available from a given
413 wind-power resource; and, prediction of power generated from a set of electric wind-turbines
414 can help proactive decisions on load-sharing on the grid. In other words, forecasting electric
415 power output from a wind-turbine source can be a viable technoeconomic support in making
416 of a successful smart-grid.

417
418 The question of reliable forecasting in such contexts of wind-power generator systems will
419 depend on the following: Mostly, the data acquired in the past (*ex post*) on the performance
420 of a wind-turbine system is pertinent to seasonal fluctuations in wind-speed and wind-
421 direction *vis-à-vis* the corresponding electric power output delivered. Normally, relevant
422 sampled-data are measured and stored (as regard the prevailing conditions of wind-speed
423 and directions in a specified period); and, the stored data is subsequently adopted for
424 predictions on the power delivery in future (*ex ante*). However, in order to make reliable
425 predictions/forecast, first a compatible algorithm should be developed relating the power
426 generated *versus* wind-speed and wind-direction details.

427
428 Hence, in the context of wind-turbine based electric-power generation outlined above, the
429 method proposed here toward *ex ante* forecasting on the underlying technoeconomics is to
430 adopt an ANN compatible to accommodate bootstrapped sample data at its input. The
431 efficacy of the strategy proposed is determined by considering limited data set availed from
432 [4] and expanded *via* bootstrapping. Hence forecast results are obtained and compared

against those of [4] in the *ex ante* states of a single variable depicting the state of wind-speed/direction.

The data adopted in forecasting of [4] conform to a large, continuous, thorough and abundantly exhaustive set on the technoeconomics of wind-power generation. Relevant forecasting provides load-sharing details of the grid complex. On the other hand, the forecast evaluated in the present method uses only a limited and sparsely sampled data set pertinent to the same database. Hence, the merit and efficacy of the proposed strategy (that uses only a limited *ex post* sampled data) *versus* the forecast results based on exhaustive *ex post* data of [4] are elucidated. The following section provides the details on experimental simulations performed on a test ANN and the results obtained thereof are presented.

6. EXPERIMENTAL SIMULATIONS: DETAILS

As mentioned above, the pursuit based on using ANNs in forecast efforts indicated in [4] relies on the ANN being trained with an exhaustive set of data available. For example in [4] relevant data refers to details on generated power fluctuations *vis-à-vis* wind-speed and wind direction gathered at 5 second and 10 minute averages. Hence, relevant simulations indicate a robust performance of the test ANN adopted. Thus, the feasibility of using ANN is now a proven technique for the application in question when an abundantly exhaustive input data is available to train the ANN as described in [4].

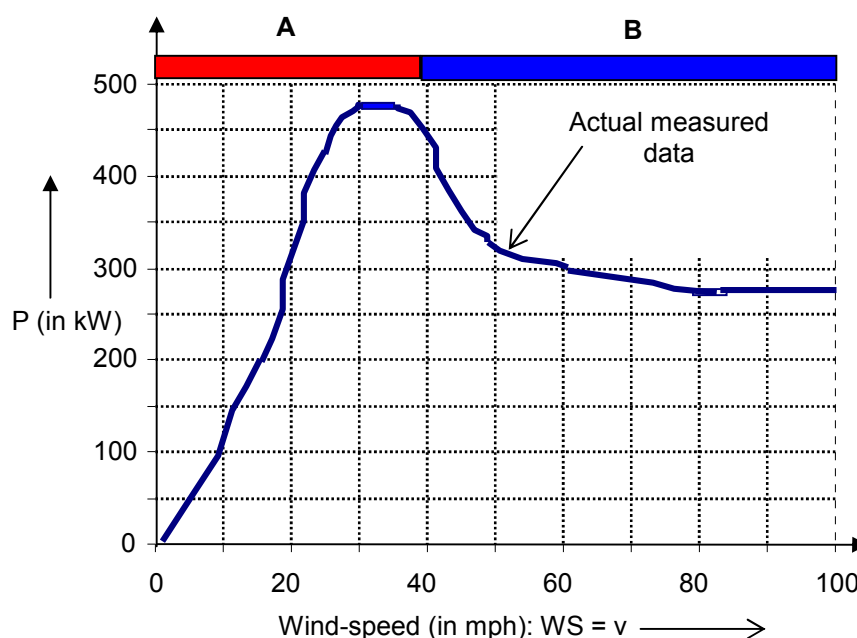
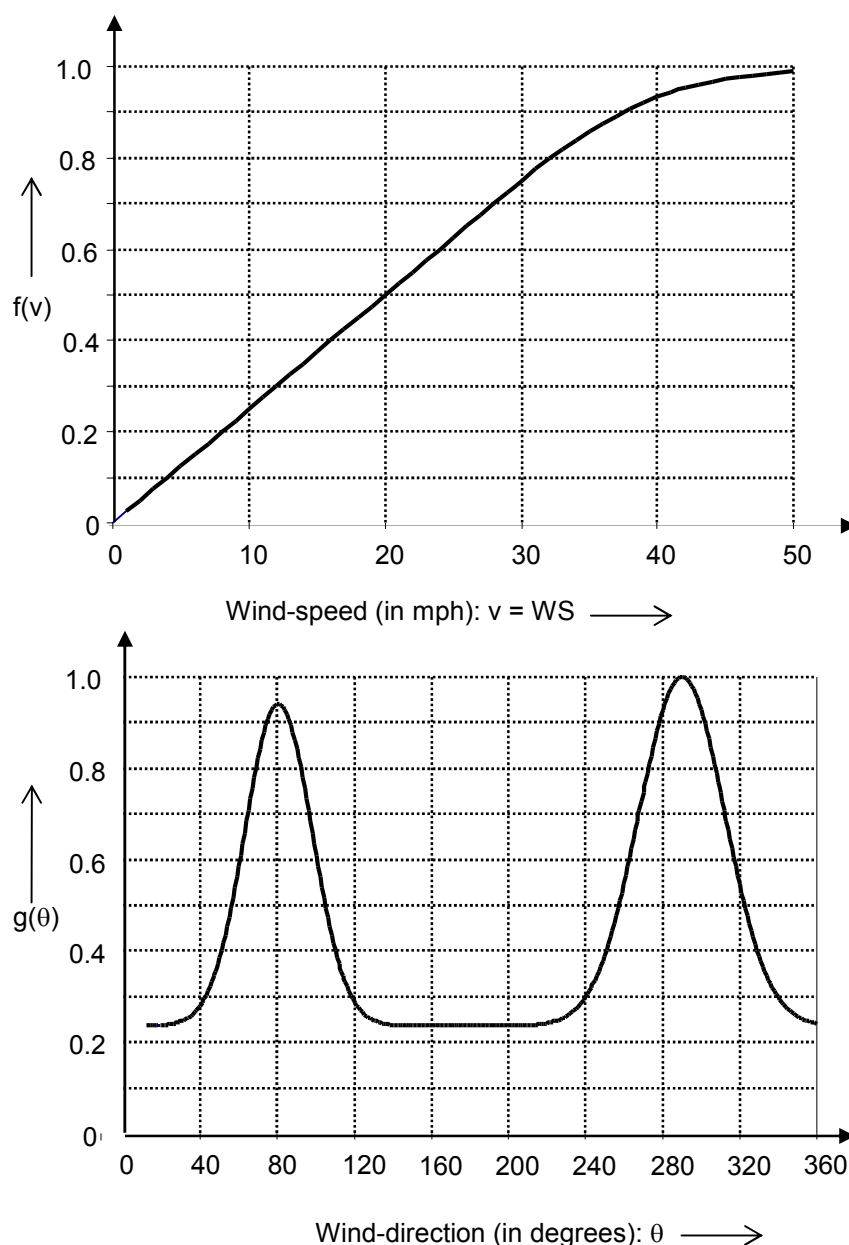


Fig. 4 Wind-power generation *versus* wind-speed averaged across an ensemble of wind directions. (A and B: Assumed *ex post* and *ex ante* regimes indicated for forecasting purposes in the present study)

However, suppose the data-set in question is sparse; that is, when it represents only a limited sample space, not so exhaustive. The query as posed earlier is that, to what extent such a limited sampled data-set can train the ANN robustly and yet yield reliable output

463 predictions. The above query is significantly important for, in many circumstances data
 464 acquisitions may not be continuously feasible nor totally exhaustive. Mostly, data is collected
 465 as samples either periodically and/or on aperiodic basis; and as such, (i) no continuous
 466 information may be available; and, (ii), the extent of ensemble data available is limited in
 467 number. Therefore, in such limited (sampled) data space, the information addressed to train
 468 the ANN may rather be inadequate. As a result, the training of ANN will not be robust
 469 enough to yield reasonably accurate predictions.
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 474 **Fig. 5 Functional relations that decide the wind-power generation (P) versus wind-**
 475 **speed (v) and wind direction (θ) and P is proportional to: $f(v) \times g(\theta)$ in normalized scale**

Hence, as mentioned earlier, attempted in this study is to invoke the concept of statistical bootstrapping and apply it to the limited data space. Then the resulting, enhanced extent of data availed from bootstrapping is used for ANN training so that the output prediction becomes more robust and reliable in practical contexts. That is, without increasing the architectural complexity, realizing a robust ANN-based prediction is studied by constructing an adequate number of bootstrapped sampled data-sets. They are then addressed as the input sets during the training phase of to test ANN. The augmented data space (derived *via* bootstrapping the available sparse data-set) and applied to the test ANN enables robust prediction performance on the output results sought.

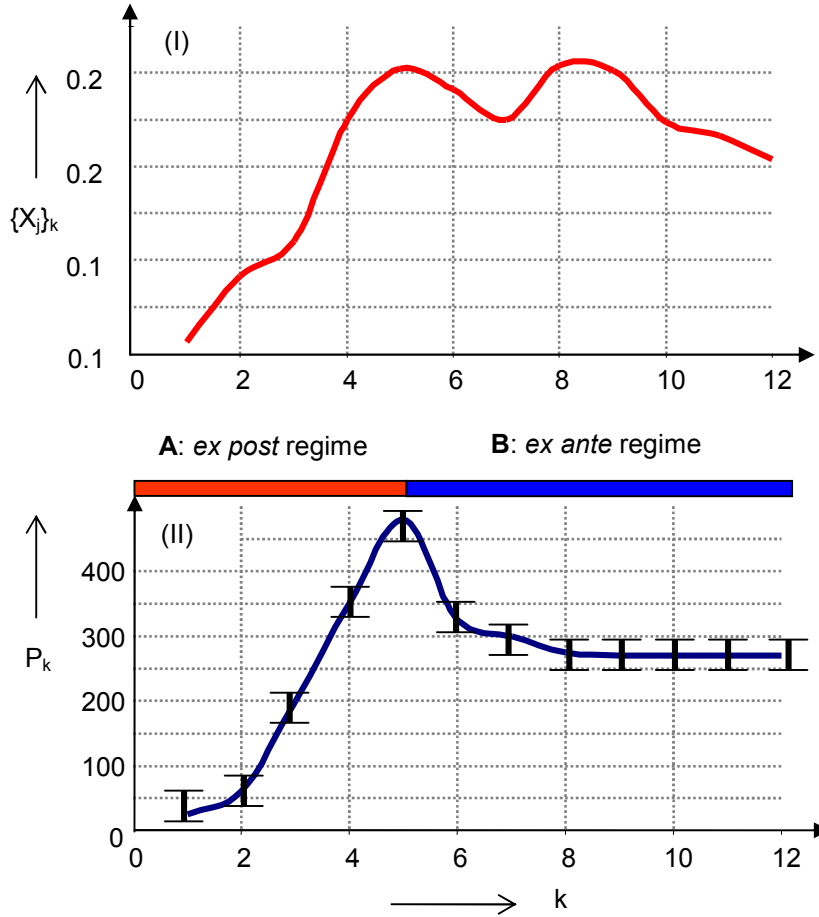


Fig. 6 (I): Input values $(X_j)_k = \{f(.) \times g(.)\}_k$ values **versus** window # k of the wind-speed. **(II)** Power delivery P_k in kW **versus** window # k . The window number k is an index representing the k^{th} sub-segment window (denoted as W_k) of the wind-speed ($v = \text{WS}$ in mph). Explicitly, W_k corresponds to the sub-segments of wind-speed sequenced in *ex post* regime as follows: ($k = 1$: $\text{WS} = 0-8$; $k = 2$: $\text{WS} = 8-16$; $k = 3$: $\text{WS} = 16-24$; $k = 4$: $\text{WS} = 24-32$; $k = 5$: $\text{WS} = 32-40$); and, the window designations for the *ex ante* regime are: ($k = 6$: $\text{WS} = 40-48$; $k = 7$: $\text{WS} = 48-54$; $k = 8$: $\text{WS} = 54-60$;; $k = 13$: $\text{WS} = 92-100$);

The data adopted in the present study is same as that in [4]. Shown in Fig. 4 is the measured wind-turbine power generated (P in kW) *versus* the average wind-speed (in mph) gathered from the measured cluster of data with varying wind directions. The combined

influence of wind-speed ($v = WS$) and wind-direction (θ) on the general trend in power generation (P) is approximately specified by a functional relation proportional to: $f(v) \times g(\theta)$ where the functions $f(\cdot)$ and $g(\cdot)$ are explicitly depicted in Fig. 5. The functions $f(\cdot)$ and $g(\cdot)$ are deduced in [4] empirically on the basis of extensive data collected in the wind-farm consistent with the power generation profile of Fig.4. In other words, these functions are predictive algorithms considered in this study on the wind-power generated *versus* v and θ and adopted in the ANN simulation experiments.

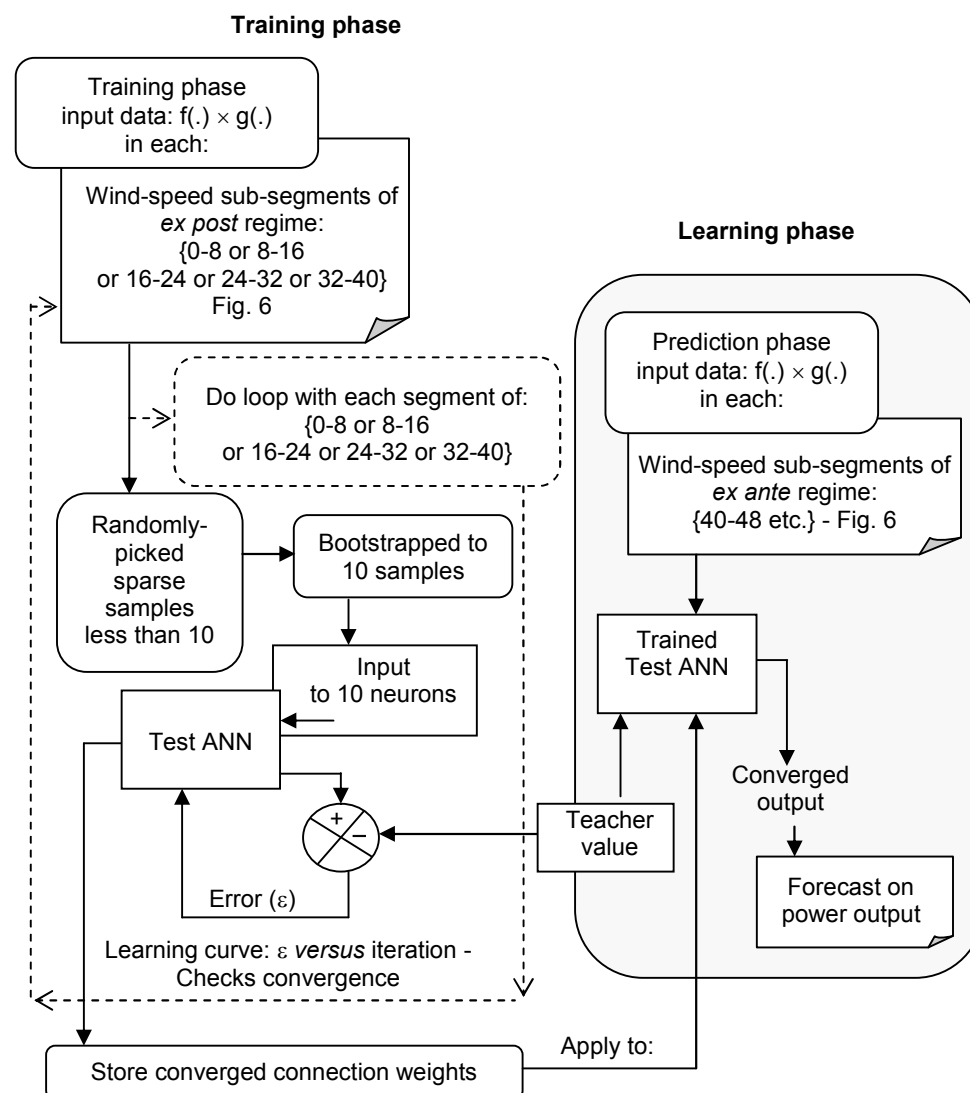


Fig. 7 Flow-chart on the procedure for constructing the bootstrapped sample-space and applying it on the test ANN in the training phase and subsequent prediction phase exercised for forecasting in the *ex ante* regime

For forecasting purposes, the stretch of data in Fig 4 is bifurcated into two assumed regimes, *ex post* (A) and *ex ante* (B) as illustrated in Fig. 4. In the assumed *ex post* regime (A), $0 \leq (WS = v) \leq 40$, a set of sparsely sampled-data are specified across a set of 5 wind-speed

segments namely, $\{v = 0-8, 8-16, 16-24, 24-32 \text{ and } 32-40\}$. Then, in each window (segment), the prevailing sparse samples (less than 10 values) are considered and enhanced to an extent of 10 *via* bootstrapping exercised on 1 or 2 or on more sparse-samples as necessary (Table 1). These 10 bootstrapped samples are then adopted as inputs to train the test ANN. Further, for each subset indicated above, the mean value of power delivery P expressed *via* the (normalized) functional relation $f(v) \times g(\theta)$ is determined and used as the corresponding teacher value in ANN simulations.

The complete procedure adopted in constructing the bootstrapped sample-space and applying it on the test ANN during training phase and enabling forecasting in the prediction phase of the *ex ante* regime is illustrated in Fig. 7.

7. RESULTS AND DISCUSSIONS

To perform the training schedule on the test ANN, an ensemble of subsets are generated with random sparse-samples followed by bootstrapping as indicated above. Table 1 lists the entire ensemble of simulated (bootstrapped) sample-space adopted in test ANN training and the corresponding details on the convergence are also presented in Table 1. Examples of relevant learning curves (deduced with *ex post* data) confirming the convergence of ANN training are presented in Figs. 8(a) - 8(e).

Indicated in Table 2 are details on the prediction phase of *ex ante* regime spanning the wind-speed sub-segments (40-48), (48-56) ..., (96-100). In each sub-segment, the converged test ANN output expressed in $\{f(.) \times g(.)\}$ is indicated and the corresponding actual and predicted values of the generated wind-power in kW are also presented. Fig.8(f) illustrates the summarized results with the corresponding percentage error observed in the predicted data.

Table 1. Example details on the training phase with *ex post* (A) data

Test ANN: Description

Multi-layer perceptron (MLP) depicting a feed-forward, multilayer architecture, which uses backpropagation algorithm in successive iterations to minimize the output error sensed with respect to a supervisory (teacher) value (Fig. 1).

Number of input neurons:	10
Number of hidden layers:	1
Number of output unit:	1
Nonlinear squashing function:	Hyperbolic tangent
Error function:	Mean-squared error (MSE)
Bias value:	0

Test ANN: Training phase with *ex post* data

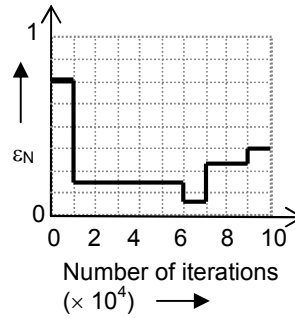
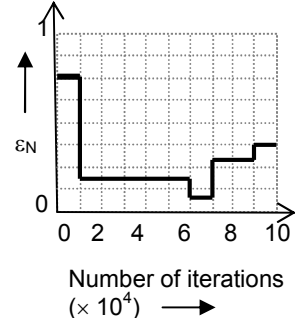
Input values $(X_j)_k$, $j = 1, 2, \dots, 10$ correspond to: $[f(.) \times g(.)]$ values known at the i^{th} instants of sample occurrence within the k^{th} sub-segment window of wind-speed (WS in mph) denoted by $(W)_k$ across the *ex post* regime divided into k -windows. Explicitly, $(W)_k$ corresponds to the sub-segments of wind-speed: $k = 1$: WS = 0-8; $k = 2$: WS = 8-16; $k = 3$: WS = 16-24; $k = 4$: WS = 24-32; $k = 5$: WS = 32-40; and, each window has 10 epochs or samples that may include bootstrapped values.

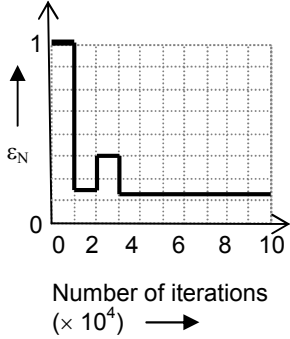
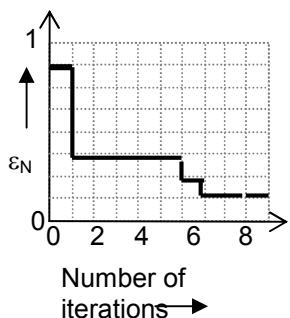
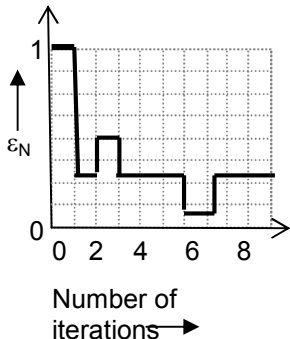
Corresponding to each window segment, a teacher value T_k is prescribed

and it is equal to: Ensemble average of $\{X_j\}_k \Rightarrow \{[f(.) \times g(.)]_j\}_k$ training data adopted in the k^{th} sub-segment of interest across the *ex post* regime

Examples of teaching schedule illustrating the convergence of the network

(The input values shown **bold** correspond to entities obtained to enhance the sparse sample-set to 10 in number *via* bootstrapping)

Window (W) _k In the <i>ex post</i> regime: ANN training phase	Input values $\{X_j\}_k$	Converged error (ϵ) ($\times 10^{-4}$) at test ANN output	(T) _k	Learning curves: Normalized error (ϵ_N) <i>versus</i> Number of iterations. (Normalization done with respect to maximum error seen at the start of the iterations)
$k = 1$ WS: 0-8 mph	0.000 0.075 0.235 0.075 0.075 0.100 0.100 0.250 0.250 0.255	0.50	0.155	 Fig. 8(a) Learning curve for $W_k=1$
$k = 2$ WS: 8-16 mph	0.025 0.025 0.100 0.235 0.235 0.235 0.235 0.235 0.250 0.250	6.80	0.198	 Fig. 8(b) Learning curve for $W_k=2$

k = 3 WS: 16-24 mph	0.025 0.025 0.100 0.235 0.235 0.235 0.235 0.235 0.250 0.250	2.40	0.250	 Fig. 8(c) Learning curve for $W_k = 3$
k = 4 WS: 24-32 mph	0.250 0.235 0.275 0.275 0.300 0.300 0.235 0.236 0.375 0.236	1.40	0.271	 Fig. 8(d) Learning curve for $W_k = 4$
k = 4 WS: 32-40 mph	0.250 0.235 0.275 0.236 0.300 0.236 0.235 0.236 0.375 0.236	2.40	0.261	 Fig. 8(e) Learning curve for $W_k = 4$

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557 **Table 2. Test ANN: Prediction phase (B: ex ante) results and forecast data on power**
 558 **generation**
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Window (W) _k In ex ante regime: ANN prediction phase	Ex ante regime: Input values {X} _j	Converged test ANN output value of: [f(.) × g(.)]	Power generated in kW	
			Actual Value [4]	Predicted via test ANN
k = 5 WS: 40-48 mph	0.250	0.272	479	470
	0.250			
	0.275			
	0.236			
	0.300			
	0.236			
	0.235			
	0.236			
	0.375			
	0.237			
k = 6 WS: 48-56 mph	0.250	0.263	325	316
	0.235			
	0.275			
	0.236			
	0.300			
	0.236			
	0.235			
	0.235			
	0.375			
	0.375			
k = 7 WS: 56-64 mph	0.250	0.250	300	285
	0.250			
	0.275			
	0.236			
	0.300			
	0.236			
	0.235			
	0.236			
	0.236			
	0.236			
k = 8 WS: 64-72 mph	0.250	0.273	275	300
	0.235			
	0.235			
	0.236			
	0.300			
	0.300			
	0.325			
	0.236			
	0.375			
	0.236			

k = 9 WS: 72-80 mph	0.250	0.271	270	290
	0.250			
	0.275			
	0.236			
	0.300			
	0.326			
	0.325			
	0.235			
	0.375			
	0.236			
k = 10 WS: 80-88 mph	0.250	0.249	270	280
	0.250			
	0.235			
	0.275			
	0.236			
	0.236			
	0.235			
	0.236			
	0.236			
	0.236			
k = 11 WS: 88-96 mph	0.250	0.243	270	280
	0.250			
	0.100			
	0.235			
	0.235			
	0.235			
	0.235			
	0.235			
	0.375			
	0.236			
k = 12 WS: 96-100 mph	0.250	0.233	270	282
	0.250			
	0.275			
	0.236			
	0.236			
	0.275			
	0.235			
	0.236			
	0.375			
	0.375			

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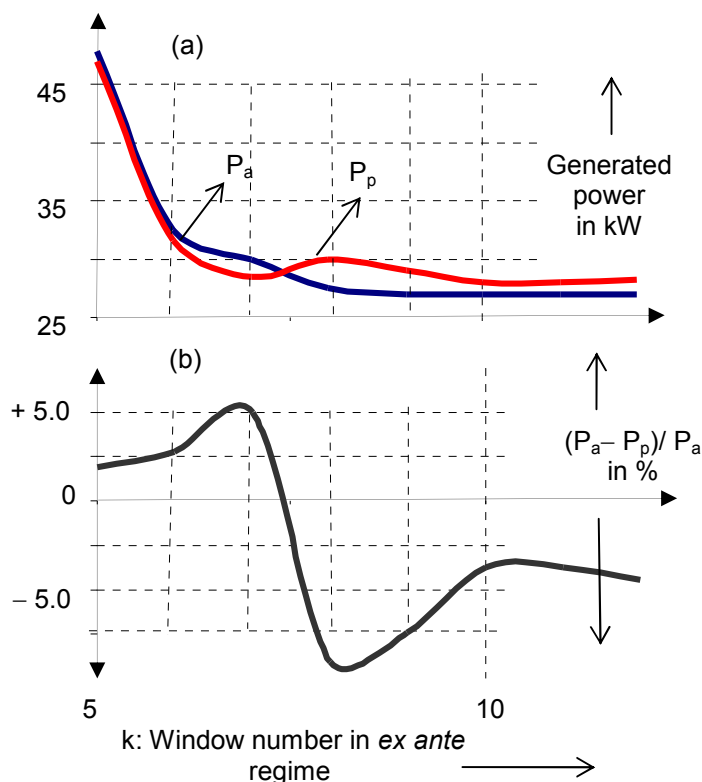


Fig. 8(f) Predicted results with the test ANN. (a) The actual power generated (P_a in kW) as in [4] and the predicted power (P_p in kW) versus window sub-segments $k = (5, 6, \dots, 12)$ as defined earlier; and (b): Percentage error of predicted result with respect to actual data of [4].

From the results presented above the following can be inferred:

- The proposed ANN strategy (of MLP architecture) is able to yield forecast projections when it is trained with an ensemble of *ex post* data
- In this context, the ANN can be exclusively designed for *ex ante* forecasting in even when the an ensemble set of sampled-data availed *ex post* is sparse and insufficient
- That is, even if the available *ex post* data samples are inadequate in number, relevant cardinality of the set can be enhanced *via* statistical bootstrapping. Then the bootstrapped data is adopted toward ANN training. Bootstrapping exercise here conforms to a sparsity recovery effort
- The associated information recovery criterion in bootstrapping is that the new samples generated should be asymptotically linear multiples and meet the Nyquist-Shannon condition [25][26]
- Once adequate samples are available (*via* sparsity recovery) and addressed as input ensembles at the test ANN, the associated pattern gets mapped on to the synoptic weights; and, when any new pattern is addressed at the input, the test ANN classifies this new input detail *vis-à-vis* the mapped pattern
- With a real world technoeconomic data on wind-power generation complex, the efficacy of the proposed approach is illustrated. For the purpose of forecasting, the wind-speed domain is bifurcated into two regimes namely, A (*ex post*) and B (*ex ante*) as illustrated in Figs. 4 and 6. The test ANN is trained with *ex post* (A) details

and the predicted results in *ex ante* (B) stretch of wind-speed are within $\pm 10\%$ of the actual value of the wind-power generated

- The associated convergence and forecast predictions are evident from the results indicated in Tables 1 and 2
- Without any loss of generality, the present method of forecast predictions can be exploited in similar technoeconomic contexts where insufficiency of data samples is observed; and, the performance of such structures can be elucidated optimally in terms of the underlying futuristic predictions (forecast projections) and the anticipated productivity across the *ex ante* regime.

8. CLOSURE

In all, the proposed BSD-ANN suggests the feasibility of assessing forecast projections effectively even with only a limited (sparse) sampled-data set available in practical technoeconomic contexts. Bootstrapping-based enhancement of sampled-data can be up to 30-40 % of the available data. The efficacy of the proposed method in the contexts of technoeconomics is illustrated with a practical real-world system wherein, sparsity recovery is done and relevant bootstrapped data sample-set is effectively applied to a test ANN for robust forecast purposes.

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