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# evoDLA: A semantic learning system for predictive cost minimization in power generation system

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**Abstract**

In this paper, we propose evolutionary deviant learning system (evoDLA) for optimal power generating systems. It is a temporally structured learning system for the predictive cost minimization task at the next time step expressed in a semantic way. Cost minimization in power generation is an assignment problem that requires the determination of the best set of operating parameters to enable generators perform optimally. Presented as an alternative to the conventional unit commitment strategies, the predictive system is designed to operate in a semi-supervised manner allowing the dynamic superimposition of linguistic memory units into the mixed-integer power system generation data. A set of representative linguistic biased integers are programmed into an equivalent fuzzy-like integer representation. These are transformed through a series of temporal deviant states and then re-transformed back into true linguistic form. Simulation studies are performed in comparison with the Long Short-Term Memory (LSTM), a proven artificial neural network (ANN) method for sequential learning tasks. The results show competitive performance with the present system and the unique capability of the novel system in inferring the optimal set of output generation parameters.

***Keywords:*** Deviant learning; Optimal power generation; Cost minimization; Unit commitment; Predictive system; Mixed integer programming

## 1. Introduction

The problem of cost minimization in power systems generation has been an active area of research till this day, and is a consequence of the unit commitment problem (UCP) which defines the requirement of finding the optimal schedules for a set of power generating units and their corresponding generating levels [1]. This also has considerable impact on the effective utilization, efficiency and forecast planning of power system generating and distribution stations. Some notable contributions in this field has been well documented in [2-4] based on mixed-integer programming; [5] and [6] using column generation approach and Zareipour et al. [7] by forecasting unit commitment using the price-responsive loads approach.

More recent efforts at solving the cost minimization problem has been researched upon with reasonable degrees of accuracy. For instance, artificial intelligence models have been developed that prescribe a solution based on a global solution space [8]. In [9], the use of genetic algorithms with Monte Carlo simulation for scheduling power outputs in a distributed generation have been carried out; Tan et al [10] used body immune algorithms for the power system schedule optimization task, and adaptive capacity unit commitment models have been implemented in [11]. Also, in a related research Deep recurrent neural networks have also recently been used in power markets with a focus on optimum storage, power efficiency, and load forecasting [21-23]. An extensive review of recent approaches can be found in [12].

As a consequence of these approaches, optimal power flow (OPF) programming software tools have been developed using ANNs and applied to an African power market [13]. The capacity (MW/MVAR loading), consumer demand satisfaction, time up/down and ramp constraints [17] are pertinent issues that are likely to be faced by the power system economic schedule managers. Thus, more robust solutions are required that handle the complexities inherent in multiple constrained problems. A typical solutions approach in this regard have also been attempted as in [17].

However, as argued in [15] true AI schemes must account for temporal states and in addition, a large number of synaptic learning units. Computing with words (CWW) also presents a possible approach for semantic understanding and reasoning which is lacking in most inference learning systems used in power systems cost minimization; the concept of true computing with words (CWW) has already been described in [14 and 15] and also more recently in [16] with promising ideas for actual real world implementations. Thus, a model for predictive and semantic cost minimization of power system generation is lacking in the literature.

The primary purpose of this paper is to develop a predictive inference learning system based on a novel cortical learning algorithm – the Deviant Learning Algorithm (DLA), with semantic capabilities for predictive cost minimization in the Nigerian power market. In particular, we focus on the temporal optimization of power system load schedules where we are interested in determining at the next time step, the optimum generation schedule in MW for a set of power system generation plant. Our proposed system model can semantically handle linguistic variables as well as numeric variables chunk-by-chunk or one-by-one as well as avoid the direct computation of the Lagrangian when not needed i.e. our sys-

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tem can further optimize the Lagrangian approach using a memory prediction framework (the DLA) and in addition this has the potential to reduce the cost of processing in an OPF programme. The DLA fulfills the principle of sparse distributed representations, bi-directional activation propagation, inhibitory competition, error-driven learning task and Hebbian learning in a biologically realistic way [19]. The LSTM algorithm have been shown to perform well on sequence learning tasks [24-26]. However, it remains to be proven if it has semantic/or linguistic capabilities for predictive power system optimization tasks.

The contributions of this study are as follows:

- The development of a novel theoretical framework/algorithm (evo-DLA) for semantic reasoning and prediction of optimum power system plant generation schedules.
- The comparative evaluation with an existing state-of-the-art neural prediction algorithm.

This paper is structured in the following order. Section 2 presents the proposed system methodology including the guiding principles based on the DLA. Section 3 provides the experimental details and a brief discussion of the results, while Section 4 concludes this paper.

## 2. Methodology for predictive cost minimization of power systems generation

The unit commitment problem is generally defined as [1, 2]:

$$\min\left(O_{\text{costs}}\right) = \sum\left\{F_{\text{costs}}, I_{\text{costs}}\right\} \tag{1}$$

where,
$F_{\text{costs}}$: fuel costs
$I_{\text{costs}}$: start-up costs
$O_{\text{costs}}$: operational costs

For the scheduling aspect we are interested in determining the best (minimal) switching time settings of generator unit(s) that satisfies the consumer load demand specifications at minimal production costs so (1) gives a general representation of this problem. Due to complexity requirements largely due to the hours taken for analytic processing of required minimum cost of operation, a reformulation based on a Danzig-Wolfe decomposition have been used by power system researchers [6]. Basically, this assumes a constant unit commitment in a reformulated unit commitment problem for diverse use case scenarios. However, this simplification do not work well in practice as unit commitment is largely variable.

### 2.1. Systems architecture description

Following a data flow modeling paradigm, the modified architecture for predictive cost minimization accounting for power system generation variability and semantic compliance is as shown in Fig. 1.

The system is basically a two station power generation system. Two manual entry blocks (Power user load stations – stations 1 and 2) are used to model real world power demand from consumers; it is expected that the power generating stations should optimally deliver power to the respective load stations. The attribute variability block captures the case of real-time or hypothetical power changing values in the system. These values are then function-fitted by a Lagrangian optimizer block with the primary purpose of synthesizing the optimal power generation schedule for the system under study.

Due to the variation in load demand and changing load profile the optimal load schedules will also vary. This has to be accounted for in the predictive system. We have succeeded in handling this issue by using a recurrent column generation program similar to that used in Shiina and Birge [2], but rather than storing the demand data in a list prior to processing, it is temporally adapted (online processed and by virtue of delay blocks) and the optimal states are only stored. This optimal states are also adaptively described in a semantic way using a semantic encoding block. For instance a power value greater than 100MW may be defined as high or very high. The predictive processor block uses the DLA to predict at the next time step, the most probable power systems generation schedule (see Fig. 1). An operator block has been added to provide an inhibitory effect on the changing load profile and power demand output functions (assumed to be active at time step, t) based on an optimal state decision block (controlled through semantic optimal power schedule requests). The output of this block is active whenever a prediction is not found from the predictive processor; it is inactive otherwise.

### 2.2. Condition for minimal unit production costs

In order to comprehend the principle of economic operation of power systems generator units, a knowledge of the conditions necessary for least costs of production. This is fundamentally based on the principles of cost change with respect to power generated as:

$$\frac{\partial O_{\text{costs}(i)}}{\partial P_{(i)}} = k_i \cdot P_{(i)} + l_i \tag{2}$$

For a given schedule at time, t, these costs vary depending on the switching state of the generator unit (ton/toff). Thus, at particular instant in time, we desire the unit that will give the net least possible state for a given scenario, say load demand. With respect to the Lagrangian multiplier, this demands an equal incremental costs of production for the units in concern:

$$\frac{\partial O_{\text{costs}(i)}}{\partial P_{(i)}} = \frac{\partial O_{\text{costs}(i-1)}}{\partial P_{(i-1)}} \tag{3}$$

### 2.3. Accounting for transmission losses in power systems generation

To effectively model the coordination of incremental production costs, we need to account for transmission losses due to the system generation; real world power generation units always present some system losses in the course of its operation.

The Lagrangian equation of constraint accounting for transmission power losses is expressed as [18, pp.385-387]:

$$\Psi\left(P_1, P_2, \ldots, P_n\right) = \sum_{j=1}^{n} P_j - P_L - P_R = \sum P_j - (P_L + P_R) = 0 \tag{4}$$

For Ct to be a minimum,

$$\frac{\partial C_{t(i)}}{\partial P_{j(i)}} - \lambda \frac{\partial \Psi}{\partial P_j} = 0 \tag{5}$$

The expression,

$$\lambda' \frac{\partial \Psi}{\partial P_j} \equiv 1 - \frac{\partial P_L}{\partial P_j} \tag{6}$$

from which,

$$\lambda' = \frac{\partial C_j}{\partial P_j}\left\{1 - \frac{\partial P_L}{\partial P_j}\right\}^{-1} \\ C_{j(t)}\left(1 - \sigma_j\right)^{-1} \tag{7}$$

The term $(1 - \sigma_j)^{-1}$ in eq. 7 is referred to as the penalty factor for station j.

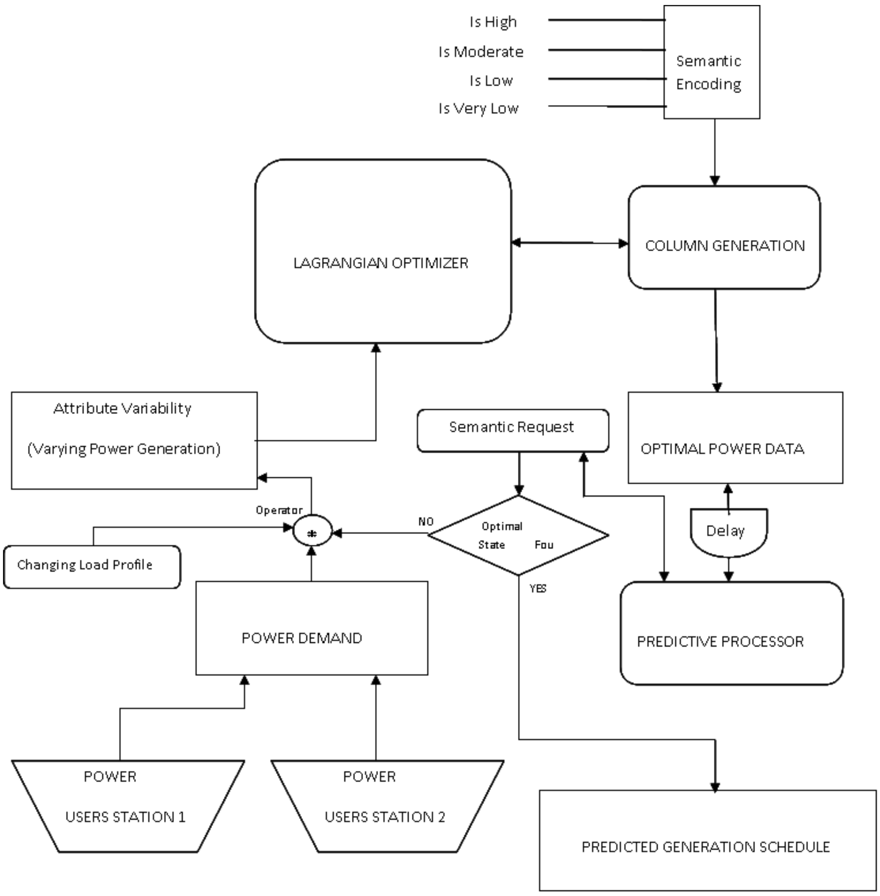


**Figure 1:** Proposed architecture for predictive cost minimization of power system generation.

## 2.4. Power system load scheduling

Given a system of power system generator sources, a convex quadratic function describing the costs of production in terms of the unit generation may be expressed as:

$$C_{t(i)} = a * P_{t(i)}^2 + b_{t(i)} P_{t(i)} + k \tag{8}$$

(9)

Considering equal power scheduling across all units,

$$C_{\text{equal}(t(i))} = a * P_{\text{equal}(t(i))}^2 + b_{t(i)} P_{\text{equal}(t(i))} + k \tag{9}$$

where,

$$P_{\text{equal}(t(i))} = \frac{P_R}{n} \tag{10}$$

The differential response of eq. 8 is represented as:

$$C'_{t(i)} = \frac{\partial C_{t(i)}}{\partial P_{t(i)}} \tag{11}$$

from which we solve for the optimal power generation at time, t, as:

$$P_{t(i)} = \frac{\left\{ C'_{t(i)} \right\}}{P_{t(i)}} \tag{12}$$

The net savings or loss may be computed by substituting (13) and (11) into (9) and (10) respectively, and then taking the net difference as:

$$C_{\text{net}(t(i))} = \sum \left( C_{t(i)} - C_{\text{equal}(t(i))} \right) \tag{13}$$

Positive values of $C_{\text{net}(t(i))}$ imply a cost saving while negative values indicates a loss.

In practice, $C_{t(i)}$ is derived from a polynomial curve-fitting process using a suitable technical computing tool. $C_{t(i)}$ is expected to vary slowly over the expected time interval and based on the power demand requirements.

## 2.5. Predictive cost minimization (PCM) using the DLA concept

In order to comprehend the methodology of PCM, we restate the UCP as a temporal sequence learning problem as follows where we do not want the unit commitment schedule to be constant. We define a scenario as a constrained set of generation parameters (fuel costs and loading) where the power demand is initially also described in linguistic terms (high, low, moderate etc.) by the expert user. For a given time instant, a different set of generation parameters is evolved. This process is repeated for several instances of time. An extension of the DLA's predictive capability is then used to perform numeric predictions in a backward additive manner as follows:

1. Train a temporal DLA state observer with a temporal sequence of optimal exemplars using the values obtained in (13) – see subsection 2.1.3. This generates a memory of deviants using the SDR architecture proposed in [20]

2. Using the nth prediction in step 1 as a deviant and the previous (n-1) deviants as standards perform an aggregated deviant operation as:

$$K_{\text{avg}}^t = \frac{\sum_{j=1}^{n} \left( K_n^t - K_{\text{seq}}^t \right)}{n} \tag{14}$$

1. Using eq. 10, compute the deviants numeric prediction as:

$$K_p^t = K_{\text{avg}}^t + K_n^t \tag{15}$$

### 2.6. Automatic programming and the DLA

Automatic programming is achieved by inducing grammatically correct structures in DLA memory system by using an adaptive and dynamic sparse distributed temporal representation (SDTR). With the STDR procedure, it is possible to implement key neural functionality – mismatch, overlap learning, reinforcement, and policy conditioning with an evolvable state in both software and eventually in hardware through special interfaces. Because the DLA encourages string to integer and integer to string transformations, character by character language encoding and semantic coding schemes is also possibility.

## 3. Results and discussion

### 3.1. Data for Experiments

Sample data for initial experiments have been obtained from the Power Holding Corporation of Nigeria (PHCN) and focus on two key injection stations in Port-Harcourt (PH) metropolis: the PH MAIN (22) and PH MAIN (24) T/S. This data is based on weekly daily load utilization and allocation obtained from 2009 to 2012. The maximum possible allocation is estimated to be approximately 210MW. The parameter ranges of the DLA (Table A1) and LSTM (Table A2) for the simulations is given in Appendix A. Synthesized power data for the experiments is given in Appendix B.

### 3.2. Experiments

Experimental studies is based on the architecture of a 2-bus power system described in [18]. Experiments have been performed in two parts; for both algorithms, the results are generated using a text processing programme i.e. the data are transformed into a textual representation prior to training and learning. The tasks here is to determine if the DLA and LSTM can correctly infer the next probable optimum power generation setting and as well perform multiple predictions. Technically, multiple predictions are possible when there is a high likelihood that two or more sequences are repeated in the learning model's current memory.

For the first part we compare the predictive abilities of the DLA with the LSTM model at default specification settings for the predictive cost minimization sequence learning task based on a pre-generated list of optimal power generation for the two stations under study. The power demand is set to vary randomly between 30MW and 210MW and the optimal sets of power generation recursively computed and trained using the scheme described in the previous section. Numeric results comparing the two models are shown pictorially in Tables 1 and 2 for the DLA and the LSTM respectively. For the second instance a linguistic label is attached to each optimal value (lingual-embedding) and the system is re-run. Due to the generative nature of the LSTM, two captures were performed. The results are shown (for first bus only) in Table 3 for the DLA and in Tables 4 and 5 for the LSTM.

For the second part, the DLA is tuned for different learning extents to determine its stabilization capability on the semantic cost minimization task. This task is essential in understanding how the DLA temporally processes data and to determine when multiple predictions occur. Simulations for learning extents from a value of 116 units to 125 units are performed in increments of 1 unit. This is shown in Fig. 2.

**Table 1:** Textual representation of linguistic prediction memories and corresponding combined future memories for the DLA.

| S.N. | Linguistic Memories (Bus 1) | Linguistic Memories (Bus 2) |
|---|---|---|
| 1 | 200000000000 | 30.68 |
| 2 | 3.34 | 21.65 |
| 3 | 31.05 | 46.92 |
| 4 | 31.08 | 46.92 |
| 5 | 31.48 | 47.52 |
| 6 | 18.93 | 30.07 |
| 7 | 25.7 | 40.3 |
| 8 | 31.08 | 46.92 |
| 9 | 31.16 | 47.04 |
| 10 | 34.67 | 52.33 |
| 11 | 12.75 | 19.25 |
| 12 | 12.55 | 18.95 |
| 13 | 12.75 | 19.25 |
| Future | 12.75 | 19.25 |
| Memories | 11.8167 | 46.92 |

**Table 2:** LSTM Model Prediction Memories and corresponding greedy argmax prediction.[a]

| S.N. | Linguistic Memories (Bus 1) | Linguistic Memories (Bus 2) |
|---|---|---|
| 1 | 19.93 | 30.07 |
| 2 | 31.48 | 19.25 |
| 3 | 31.16 | 19.25 |
| 4 | 20.32 | 18.95 |
| 5 | 19.93 | 52.33 |
| Future | 31.08 | 46.92 |
| Memories | 12.75 | |

[a] argmax is based on a greedy prediction scheme used in deep recurrent LSTM networks

**Table 3:** Textual representation of linguistic prediction memories and corresponding combined future memories for the DLA for the semantic encoding task.

| S.N. | Linguistic Memories (Bus 1) | Interpretations |
|---|---|---|
| 1 | 20.32 | Low |
| 2 | 14.35 | Very Low |
| 3 | 31.08 | Moderate |
| 4 | 31.08 | Moderate |
| 5 | 31.48 | Moderate |
| 6 | 19.93 | Low |
| 7 | 26.70 | Moderate |
| 8 | 31.08 | Moderate |
| 9 | 31.16 | Moderate |
| 10 | 34.67 | Moderate |
| 11 | 12.75 | Very Low |
| Future | 12.75 | Very Low |
| Memories | 31.08 | Moderate |

**Table 4:** First captured LSTM Model Prediction Memories and corresponding greedy argmax prediction for the semantic encoding task.

| S.N. | Linguistic Memories (Bus 1) | Interpretations |
|---|---|---|
| 1 | 12.75 | Moderate |
| 2 | 12.75 | Moderate |
| 3 | 19.93 | Very Low |
| 4 | 12.75 | Very Low |
| 5 | 12.55 | Moderate |
| Future Memories | 12.75 | Very Low |

**Table 5:** Second captured LSTM Model Prediction Memories and corresponding greedy argmax prediction for the semantic encoding task.

| S.N. | Linguistic Memories (Bus 1) | Interpretations |
|---|---|---|
| 1 | 31.08 | Very Low |
| 2 | 31.48 | Very Low |
| 3 | 19.93 | Moderate |
| 4 | 31.1 | Moderate |
| 5 | 31.16 | Very Low |
| Future Memories | 31.08 | Moderate |

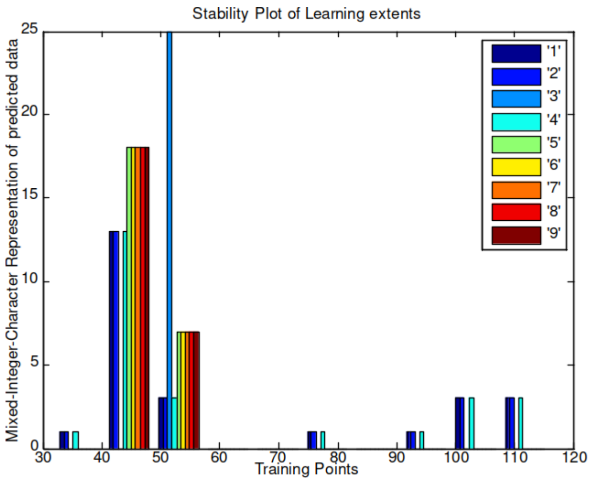


**Figure 2:** Histogram plot of the DLA's predictions for the semantic cost minimization task with varying learning extents for Bus 1.

### 3.3. Discussion

Interestingly, the two predictive systems delivered similar results.

For the first experiments, the LSTM and DLA results are competitive with the DLA remembering most (with more memory elements in its recognition list; Table 1) and performing multiple predictions on both buses while the LSTM remembering least and was unable to perform multiple predictions on second bus (Table 2). This effect can be attributed to a phenomenon called the "perplexity" which determines the degree of surprise seen by a predictive network at its next prediction move. For the semantic part of the first experiment, the results are more challenging due to the need to learn both words and the numeric predictions. However, both algorithms still fared reasonably well on the task at hand with the DLA accumulating all learned recognition in a single capture (Table 3) while the LSTM required two possible captures for learning the most likely predictions (Tables 4 and 5).

For the second part of the experiments, variations are observed for learning extents less than 121 units. However, the DLA learning network starts to stabilize with learning extents from 121 (5) to 125 (9) – see Fig. 2. Thus, increasing the learning extent improves the stabilization ability of the DLA.

## 4. Conclusion and recommendations

Predictive power systems cost minimization for a 2-bus power generation system have been performed using data from a case study area in Nigeria with optimal power data obtained using a column generation approach and semantically transformed to make it more intuitive. The generated optimal power plans is then fed to two predictive AI models (the DLA and LSTM) for comparative predictive simulation of the most likely future power schedule for the study location. The DLA showed a competitive performance when compared with the LSTM network for the optimal sequence learning task and was able to outperform the LSTM on the second bus. It also requires the tuning of a single parameter which is more cost-effective than conventional deep learning algorithms. In addition, using the presented approach with variational learning extent, it was possible to temporally evolve a sparse set of optimal power values and store them later on for semantic predictions. The proposed approach can be useful as a compensatory predictive tool in power systems optimization tasks to reduce the cost and computational expense of the Lagrangian and other conventional mixed-integer programming approaches.

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## Appendices

### A. Parameters for the LSTM and the DLA

A1. LSTM parameters.

| Parameter | min | Max |
|---|---|---|
| Hidden sizes | 20×20 | 20×20 |
| Character size | 5 | 5 |
| Learning Rate | 0 | 0.01 |
| L2 Regularization Strength | 1E-06 | 1E-06 |
| Clip Value | 5E-06 | 0.05 |
| Softmax sample temperature | 0 | 0.1 |

A2. DLA parameters.

| Parameter | min | max |
|---|---|---|
| Learning extent | 121 | 125 |
| Time limit | 10 | 10 |
| Initial permanence value | 0 | 0 |
| Store threshold | 120 | 120 |
| Tolerance constraint | 0.05 | 0.05 |

### B. Synthesized optimal data for experiments

B1. Sequence training data.

| Time Sequence | Optimal Power Values (Bus1) | Optimal Power Values (Bus2) |
|---|---|---|
| | 20.32 | 30.68 |
| 1 | 14.35 | 21.65 |
| 2 | 31.08 | 46.92 |
| 3 | 31.08 | 46.92 |
| 4 | 31.48 | 47.52 |
| 5 | 19.93 | 30.07 |
| 6 | 26.7 | 40.3 |
| 7 | 31.08 | 46.92 |
| 8 | 31.16 | 47.04 |
| 9 | 34.67 | 52.33 |
| 10 | 12.75 | 19.25 |
| 11 | 12.55 | 18.95 |
| 12 | 12.75 | 19.25 |
| 13 | 12.75 | 19.25 |