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Solving Linear Programming Problem using ANN based Hybrid Model

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ABSTRACT: The systems analysts and researchersoften find difficult to include all possible constraints although some of themmay not be binding at the optimal solution. The presence ofredundant constraints does not alter the optimum solution(s),but may consume extra computational effort.But accuracy of the LPproblems goes down due to this reduction of loops andconstraints. To achieve optimality in accuracy and also incomputational effort, we propose a modelcalled Hybrid model using ANN, it trains the constraint and parameter beforeapplying the formal methodology. Artificial neural network (ANN) has been used formany years in sectors and disciplines like medical science,defense industry, robotics, electronics, economy, forecasts, etc.The learning property of ANN in solving nonlinear and linear complex problems called for its application to forecastingproblems.

KEYWORDS: Linear Programming, ANN(Artificial Neural Network), Redundant Constraints, Load Forecasting, Training Parameters.

I. INTRODUCTION

A linear programming problem consists of a linear function to be maximized or minimized subject to certain constraints in the form of linear equations or inequalities. Linear programming (LP) is one of the simplest ways to perform optimization. It helps you solve some very complex optimization problems by making a few simplifying assumptions. As an analyst you are bound to come across applications and problems to be solved by Linear Programming. Linear programming problems arise in a wide variety of scientificand engineering fields including regression analysis,functionapproximation, signal processing, image restoration, parameterestimation, filter design, robot control, etc. Linear Programming Problems aremathematicalmodels used to represent real life situations inthe form of linear objective function and constraints variousmethods are available to solve linear programming problems.When formulating an LP model, systems analysts andresearchers often include all possible constraints althoughsome of them may not be binding at the optimal solution. Thepresence of redundant constraints does not alter the optimumsolution(s), but may consume extra computational effort.Many researchers have proposed algorithms for identifyingthe redundant constraints in LP models.The widely used methodology for LP problems is revisedsimplex method, a univariate search technique. It suffers thedrawback of slow convergence with the tendency of variablepopping in and out of the basis matrix. The numbers ofiterations are more and increase in computational effort andtime.This gives wide scope to a search of new algorithm. Inthe bounded complex algorithm [3] a univariate searchtechnique is adopted, but the entering variables are arrangednot only based on the maximum contribution if that variableto the objective function but also on the type of theconstraints. Once the priority arrangement of the promisingvariables is obtained the iterations are performed as in theSimplex Method by selecting a leaving variable based onbounds of the variables.Redundancies, if any, in the LP model will wastecomputational effort.

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II. RELATED WORKS

a) Complex Algorithm

Very often a linear programming problem may have some or all variables bounded with lower and upper limits in addition to the given constraints. The lower and upper limits can represent the minimum and maximum demands for certain products to solve this kind of these problems a special kind of technique known as a bounded variable simplex method is available. A new algorithm is presented to solve linear bounded variable problems whose constraints coefficient is non-negative. In this method the variable are arranged according to their total contribution to the objective function as was done in solving linear programming problem.

1. If any variable has a lower bound. Then substitute $X^1 = L + X$.
2. Determination of entering Vector P_j

$$Z_j - C_j = (1C_BB^{-1})\begin{pmatrix}-C_J\\ P_j\end{pmatrix}$$

If theobjective function is maximization a variable having $(Z_j - C_j)$ value as negative is Promising variable. If the objective function is maximization a variable having $(Z_j - C_j)$ value as positive is Promising variable.

3. Determination of leaving vector P_r when the entering vector is P_j and the current basis matrix B_c, the leaving vector must correspond to a $\theta_o = \min[\theta_1, \theta_2, \mu_j]$ where

$$\theta_1 = \min_k \left(\frac{B^{-1}P_o}{\alpha_{kj}}; \alpha_{kj} > 0\right)$$

where$\alpha_{kj}=B^{-1}Pj$, K = 1,2, ... , m

$$\theta_2 = \min_k \left(\frac{\mu_{k-}(B^{-1}P_o)}{\alpha_{kj}}; \alpha_{kj} < 0\right)$$

4. After selecting the leaving variable using the above condition the changes in the current basis solution can be effected as follows:

(a) If $\theta = \theta_1$ which correspond i = r than variable X_j enters the basis while the variable corresponds to $(B^{-1}P_o)_r$ leaves the basis. Update M^{-1} using step 5.

(b) If $\theta = \theta_2$ then X_j enters the basis and the variable $(B^{-1} P_o)_r$ leaves the basis. When $(B^{-1} P_o)_r$ is non-basic, its value must be zero. To achieve this put $(B^{-1} P_o)_r = \mu_r - (B^{-1}P_o)_r^1$ and P_o becomes $P_o^1 = P_o - \mu_j P_j$ and update M^{-1} using step 5.

c) If $\theta = \mu_j$ then put $X_j = \mu_j - X_j^1$ then entering variable is non-basic at $X_j = \mu_j$, there is no variable leaving the basis. But it creates the following changes $P_j^1 = P_j$ and P_o becomes $P_o - \mu_j P_j$ and $Z_j - C_j = Z_j - C_j$.

5. Construction of M^{-1}

Obtain the column vector η for the leaving $X_j$defined by

$$\eta = \begin{bmatrix} Z_J C_j \\ B^{-1}P_j \end{bmatrix}$$

6. If the list of ordered variable is exhausted then go to step 7, else go to step 2.
7. If any vector enters at its upper bound take the negated column then go step 2, else terminate the process.

b)Identification of Redundant Constraints

Redundant constraints are the constraints that can beomitted from a system of linear constraints without changingthe feasible region.

Consider the following system of *m* linear inequality constraints and *n* variables $(m \geq n)$:

$AX \leq b, X \geq 0$ (1)

where$A \in Rm\times n$, $b \in Rm$, $X \in Rn$and $0 \in Rn$.

The feasible region *S* associated with system (1) is defined

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As$S = \{X \in Rn/AX \leq b, X \geq 0\}$.
Redundant constraints in system (1) do not play a role indetermining the feasible region S.
To define redundant inequality constraints more formally,we denote for any fixed $k \in (1, 2, 3, . . . , m)$, $Sk= \{X \in Rn/AiX\leq bi, X\geq 0\ \forall i \neq k\}$.
The kth constraint $AkX\leq bk$ $(1 \leq k \leq m)$ is a redundantinequality in system (1) if and only if $Sk= S$.

III. PROPOSED ALGORITHM FOR OPTIMALITY TO IMPROVE THE ACCURACY WITH TRAINING AND LEARNING OF PARAMETERS AND CONSTRAINTS USING ANN.

A most excellent algorithm must be optimal in bothcomputational effort and accuracy. All the abovemethodologies concentrated only on achieving bestcomputational effort.Whereas accuracy of these systemsmay goes down due to reducing number of constraints andnumber of iteration. To achieve optimality in computationaleffort and also in accuracy, we proposed a hybrid algorithmicstructure.If we reduce number of iterations, the time complexitybecome optimal, but the accuracy of the system has reduced.To improve the accuracy, we suggested training and learningof parameters and constraints. This training is possible in realworld application by applying artificial neural network(ANN).The ANN has applied for various applications topredict forecasting of parameters, constraints and also toobtain optimality in real world parameters. To proceedfurther, we consider a real world application, for ex. Loadforecasting. Load forecasting is essential in the electricitymarket for the participants to manage the market efficientlyand stably. However, the electric power load forecastingproblem is not easy to handle due to its nonlinear andrandom-like behaviors of system loads,weather conditions,and variations of social and economic environments, etc.Many studies have been reported to improve the accuracy ofload forecasting using the conventional methods such asregression-based method [4], Kalman filter [5], andknowledge-based expert system [6]. However, thesetechniques have a possibility to lack the accuracy ofprediction with the higher load forecasting errors in someparticular time zones, which are, for example, the weekdaysof the summer season, weekend, and/or Monday. Toovercome this problem, the computational intelligencetechniques [4]–[13], which are the fuzzy systems andartificial neural networks [14,15,16] have been investigatedin the past decade as an alternative to the conventionalmethods.

THE NEURAL NETWORK TRAINING PROCESS:
The Training goal was set at 0 so as to ensure zero toleranceto network computational errors. The transfer functions usedwere the log-sigmoid or tan-sigmoid in the Hidden layerneurons while the Purelin function was used in the outputlayer neurons so as not to constrain the output's values. Thelearning function used is the default steepest gradientdescent method.TheLevenberg-Marquardt learningfunction was used as it has a better learning rate comparedto the other available functions in forecasting problems [17].The training function used was the steepest gradient descentfunction and in some tests the steepest gradient descentmethod with momentum. The maximum number of epochswas set to 1000 which is the default value. Finally, thelearning rate was also set to the default value and left to adjust automatically as the training made progress.

III (a) Existing Algorithm

Step I. If the predicted day is belonging to a summerseason, go to step 4). Otherwise, it is the day on spring, fall,or winter seasons.
Step II. Construct input information using the load dataduring three days (which are subject to Monday throughFriday) before the predicted day.
Step III. Forecast the maximum load using the exponentialsmoothing method.
Step IV. In case that the predicted day belongs to a summerseason, the temperature sensitivities are computed using thevariations of the load and temperature between the predicted
day and its one previous day.
Step V. Forecast the maximum load with the temperaturesensitivities calculated in step 4). After taking the above steps,the normalized value of the 24hourly loads is calculated from the data obtained from theload during the previous three weeks of the predicted day.Thereafter, the 24 hourly loads of the day are forecasted fromthe normalized value.

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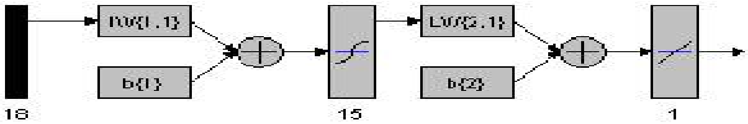

Figure.1 Shows Neural Network for Load Forecasting

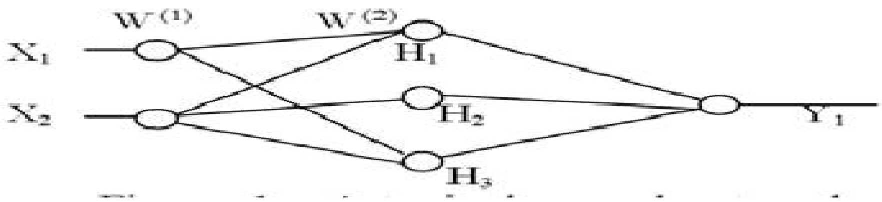

Figure.2Shows a Typical Neural Network

III (b) Our Proposed Algorithm(Model)

Step I. If the predicted day / time are belonging to class-1environment, go to step 4. Otherwise, it is class-2environment.
Step II. Construct input information using the inputparameters and constraints using any formal or conventionalmethods like complex algorithm and or identifying redundantconstraints before the predicted day or time.
Step III. Forecast the appropriate parameters.
Step IV. In case that the predicted day or time belongs to aclass-1 situation, the value of parameters may vary.
Step V.Forecast the appropriate parameters with thephysical sensitivities calculated in step 4. After taking theabove steps, the normalized value of parameters is calculatedfrom the data obtained. Thereafter, the parameters for anyclass of situation are forecasted from the normalized value.

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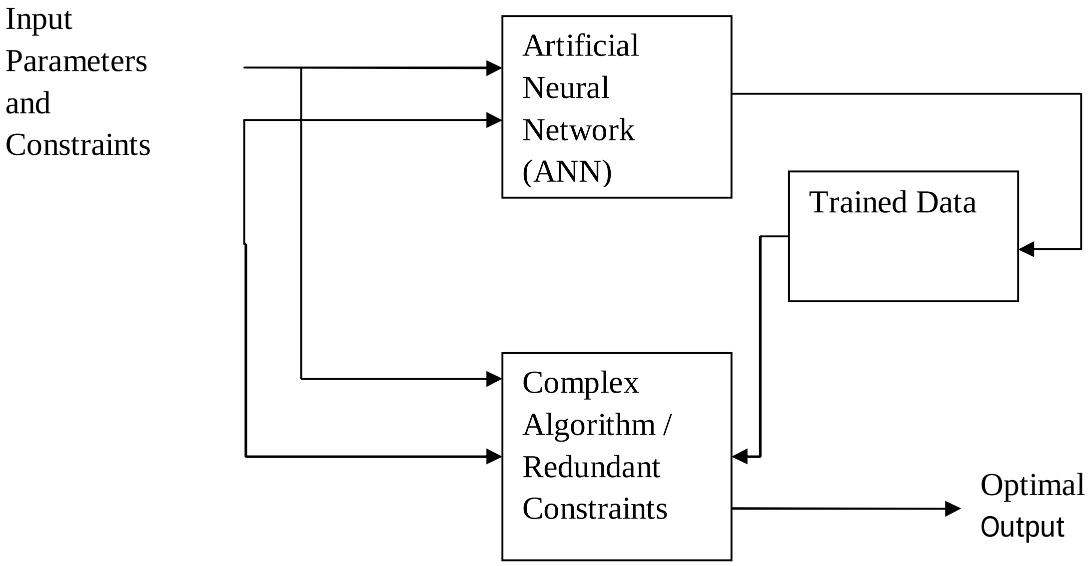

Figure.3 Shows block diagram of the Proposed Method

IV. RESULTS OF THE PROPOSED MODEL WITH TRAINING AND LEARNING (PARAMETERS AND CONSTRAINTS) BY APPLYING ANN

The proposed hybrid model that improvesthe accuracy of bounded variables in linear programmingproblem model by suggesting the training and learning ofparameters and constraints. This training is possible in realworld application by applying artificial neural network. I believe, theproposed hybrid modelshows increased performance in accuracy and efficiency.The Hybrid model must be optimal in both computational effort and accuracy. All the above methodologies concentrated only on achieving best computational effort and reduce time whereas, accuracy of these systems may go down due to reducing number of constraints and number of iteration. To achieve optimality in computational effort and also in accuracy, I proposed a model called Hybrid model using neural network with training model for optimization of parameters in a real time Linear Programming Problem. These are the results which I got from the training phase of the network.

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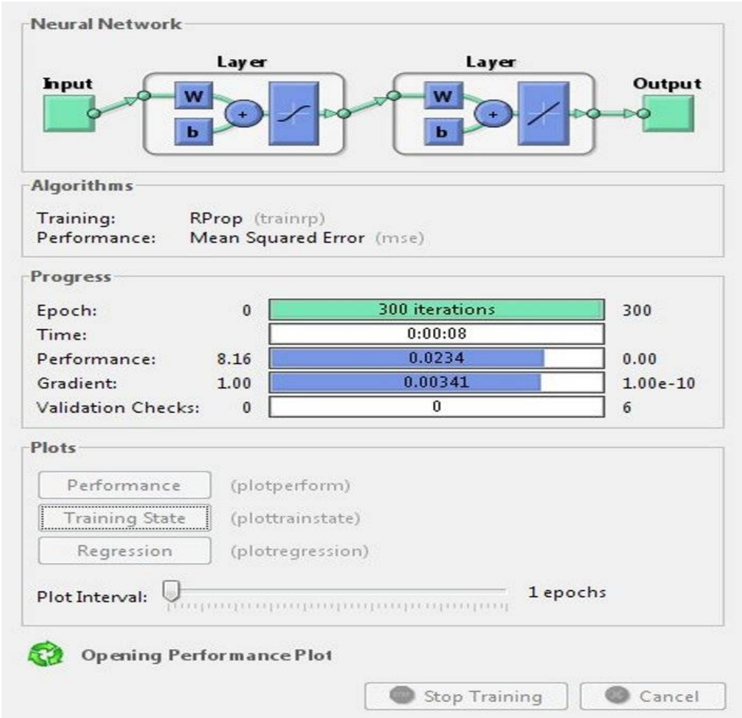

Figure: 4 Shows the training phase

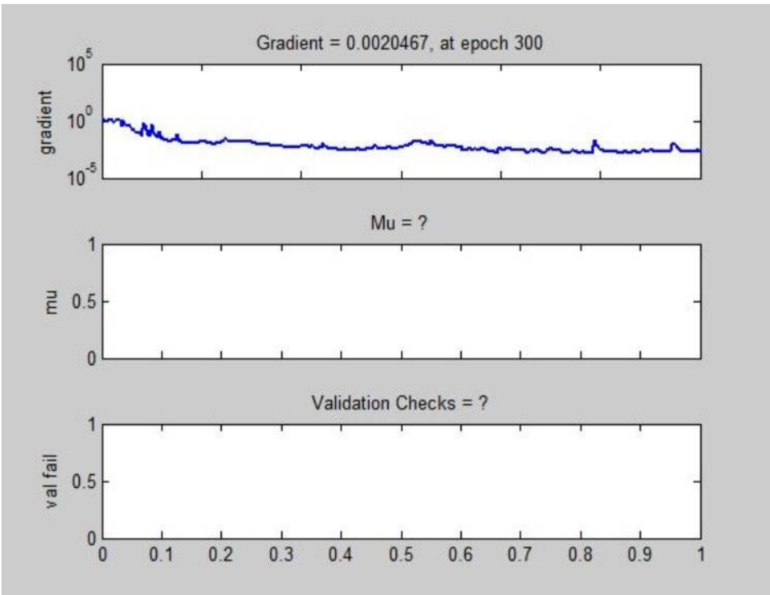

Figure: 5 Shows the training state of the network

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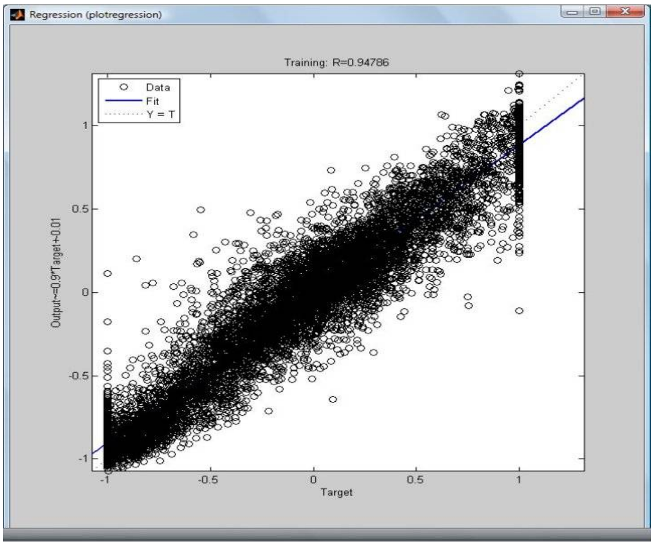

Figure: 6 Shows the Regression plot

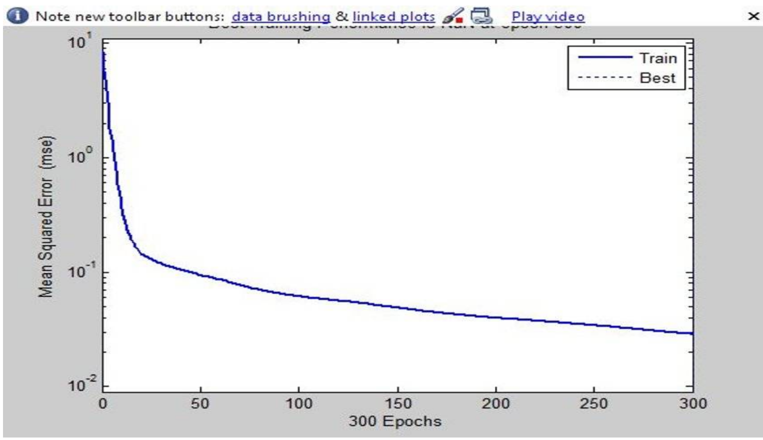

Figure: 7 Plot Performance of the Training State

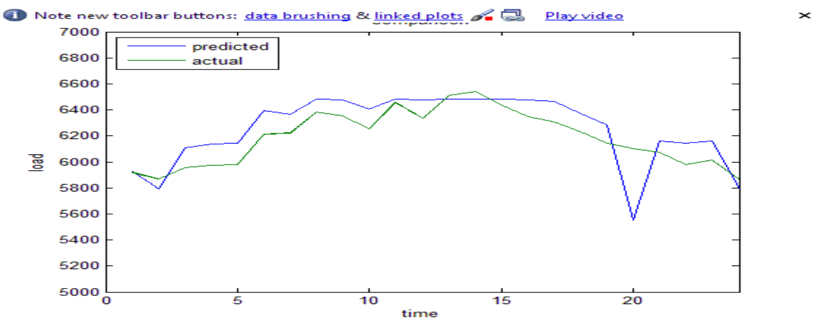

Figure.8Shows testing phase with trained and learned values for optimization.

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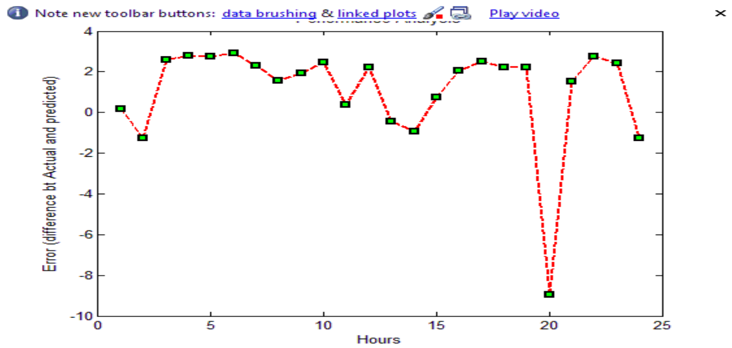

Figure.9Shows error plot difference between actual and predicted values

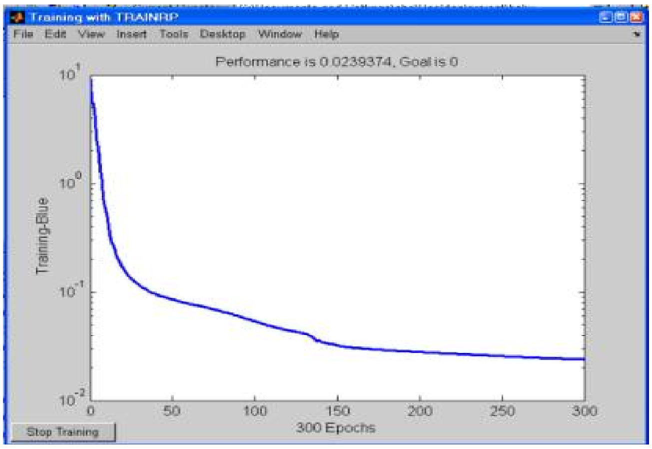

Figure.10Shows back propagation in bounded variables andredundant constraints

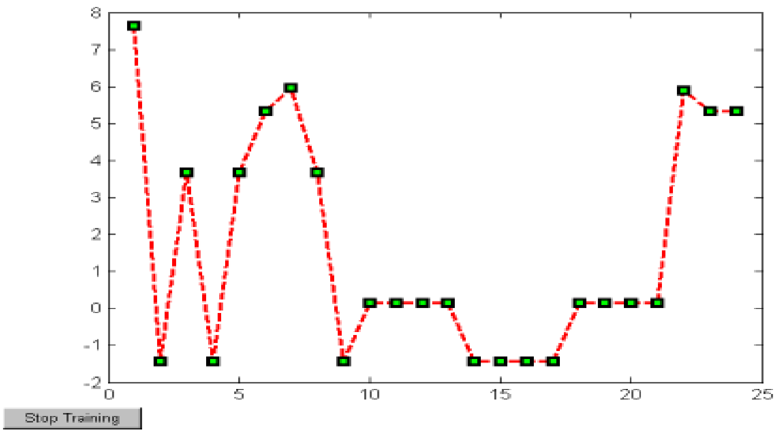

Figure: 11 Showserror rate in Linear Programming Problem Model

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V. CONCLUSION

The Hybrid modelwhich I had developed improves the accuracy of bounded variables in Linear Programming Problem model by suggesting the training and learning of parameters and constraints. The Training is possible in applications by applying Artificial Neural Network. I believe, the proposed structure shows increased performance in accuracy. The Hybrid Algorithmic Structure must be optimal in both computational effort and accuracy. All the above methodologies concentrated only on achieving best computational effort. The accuracy of these systems may go down due to reducing number of constraints and number of iteration. To achieve optimality in computational effort and also in accuracy, I proposed a Hybrid Algorithmic (model) to improve the accuracy of variables in any Linear Programming Problems.

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BIOGRAPHY

L.R. Arvind Babu was born in Cuddalore, 1975, he obtained B.E., in Instrumentation Engineering and M.Sc., Information Technology from Annamalai University in 1998 and 2001 respectively,and also obtained doctoral degree(Ph.D.) in Computer Science and presently he is working as Assistant Professorin the department of Computer & Information Science, Annamalai University, Annamalainagar-608002 for the past 18 years.