Artificial Neural Network Based Hybrid Algorithmic Structure for Solving Linear Programming Problems

L.R. Arvind Babu and B.Palaniappan

Abstract—**Linear Programming Problems are mathematical models used to represent real life situations in the form of linear objective function and constraints various methods are available to solve linear programming problems. When formulating an LP model, systems analysts and researchers often include all possible constraints although some of them may not be binding at the optimal solution. The presence of redundant constraints does not alter the optimum solution(s), but may consume extra computational effort. Redundant constraints identification methods are applied for reducing computational effort in LP problems. But accuracy of the LP problems goes down due to this reduction of loops and constraints. To achieve optimality in accuracy and also in computational effort, we propose an algorithm, called, Hybrid Algorithm, it trains the constraint and parameter before applying the formal methodology.**

Index Terms—**Linear Programming , Redundant Constraints, Load Forecasting , Training Parameters.**

I. INTRODUCTION

Linear programming (LP) is one of the most important techniques used in modeling and solving practical optimization problems that arise in industry, commerce, and management. Linear Programming Problems are mathematical models used to represent real life situations in the form of linear objective function and constraints various methods are available to solve linear programming problems.

When formulating an LP model, systems analysts and researchers often include all possible constraints although some of them may not be binding at the optimal solution. The presence of redundant constraints does not alter the optimum solution(s), but may consume extra computational effort. Many researchers have proposed algorithms for identifying the redundant constraints in LP models.

The widely used methodology for LP problems is revised simplex method, a univariate search technique. It suffers the drawback of slow convergence with the tendency of variable popping in and out of the basis matrix. The numbers of iterations are more and increase in computational effort and time. This gives wide scope to a search of new algorithm. In the bounded complex algorithm [12] a univariate search technique is adopted, but the entering variables are arranged not only based on the maximum contribution if that variable to the objective function but also on the type of the constraints. Once the priority arrangement of the promising variables is obtained the iterations are performed as in the

Simplex Method by selecting a leaving variable based on bounds of the variables.

Redundancies, if any, in the LP model will waste computational effort. In fact, there is a wide literature on the detection and elimination of redundant constraints in LP models [1–11]. Heuristic approach [13] is using an intercept matrix to identify redundant constraints prior to the start of the solution process. In this heuristic approach, tendency of variables to pop in and pop out of the basis is eradicated after eliminating the redundancies. The eradication of pop-in and pop-out substantially reduces the number of iterations. A significant reduction in the computational effort is achieved for LP problems of different sizes in heuristic approach.

II. REDUNDANT CONSTRAINTS AND COMPLEX ALGORITHM

A. Identification of Redundant constraints

Redundant constraints are the constraints that can be omitted from a system of linear constraints without changing the feasible region.

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

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

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 as

$$S = \{X \in Rn/AX \leq b, X \geq 0\}.$$

Redundant constraints in system (1) do not play a role in determining the feasible region S.

To define redundant inequality constraints more formally, we denote for any fixed $k \in (1, 2, 3, \ldots, m)$, $S_k = \{X \in Rn/AiX \leq bi, X \geq 0 \; \forall \, i \neq k \}$.

The kth constraint $A_k X \leq b_k$ *(1 ≤ k ≤ m)* is a redundant inequality in system (1) if and only if $S_k = S$.

B. 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

$$Z_j\text{-}C_j = \begin{pmatrix} 1 & C_B B^{-1} \end{pmatrix} \begin{pmatrix} -c_j \\ P_j \end{pmatrix}$$

If the objective function is maximization a variable having $(Z_j\text{-}C_j)$ value as negative is Promising variable. If the objective function is maximization a variable having $(Z_j\text{-}C_j)$ 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

$$\theta_0 = \min\left[\theta_1, \theta_2, \mu_j\right] \text{ where}$$

$$\theta_1 = \min_k \left(\frac{B^{-1}P_0}{\alpha_{kj}}; \alpha_{kj} > 0 \right)$$

Where $\alpha_{kj} = B^{-1}P_j, K = 1, 2, \ldots\ldots, m$

$$\theta_2 = \min_k \left(\frac{\mu_k - (B^{-1}P_0)}{\alpha_{kj}}; \alpha_{kj} < 0 \right)$$

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 $(B^{-1}P_0)_r$ leaves the basis. Update M^{-1} using step 5.

   b) If $\theta = \theta_2$ then X_j enters the basis and the variable $(B^{-1}P_0)_r$ leaves the basis. When $(B^{-1}P_0)_r$ is non-basic, its value must be zero. To achieve this put $(B^{-1}P_0)_r = \mu_r - (B^{-1}P_0)_r^1$ and P_0 becomes $P_0^1 = P_0 - \mu_j P_j$ and update M^{-1} using step 5. 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_0 becomes $P_0 - \mu_j P_j$ and $Z_j\text{-}C_j = Z_j\text{-}C_j$.

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.

III. HYBRID ALGORITHM

A most excellent algorithm must be optimal in both computational effort and accuracy. All the above methodologies concentrated only on achieving best

computational effort. Where as accuracy of these systems may goes down due to reducing number of constraints and number of iteration. To achieve optimality in computational effort and also in accuracy, we proposed a hybrid algorithmic structure.

If we reduce number of iterations, the time complexity become optimal, but the accuracy of the system has reduced. To improve the accuracy, we suggested training and learning of parameters and constraints. This training is possible in real world application by applying artificial neural network (ANN).The ANN has applied for various applications to predict forecasting of parameters, constraints and also to obtain optimality in real world parameters. To proceed further, we consider a real world application, for ex. Load forecasting. Load forecasting is essential in the electricity market for the participants to manage the market efficiently and stably. However, the electric power load forecasting problem is not easy to handle due to its nonlinear and random-like behaviors of system loads, weather conditions, and variations of social and economic environments, etc. Many studies have been reported to improve the accuracy of load forecasting using the conventional methods such as regression-based method [14], Kalman filter [15], and knowledge-based expert system [16]. However, these techniques have a possibility to lack the accuracy of prediction with the higher load forecasting errors in some particular time zones, which are, for example, the weekdays of the summer season, weekend, and/or Monday. To overcome this problem, the computational intelligence techniques [16]–[24], which are the fuzzy systems and artificial neural networks[19,22,27], have been investigated in the past decade as an alternative to the conventional methods.

24-hour daily load forecasting is as follows:

Step 1). If the predicted day is belonging to a summer season, go to step 4). Otherwise, it is the day on spring, fall, or winter seasons.

Step 2). Construct input information using the load data during three days (which are subject to Monday through Friday) before the predicted day.

Step 3). Forecast the maximum load using the exponential smoothing method.

Step 4). In case that the predicted day belongs to a summer season, the temperature sensitivities are computed using the variations of the load and temperature between the predicted day and its one previous day.

Step 5). Forecast the maximum load with the temperature sensitivities calculated in step 4). After taking the above steps, the normalized value of the 24

hourly loads is calculated from the data obtained from the

load during the previous three weeks of the predicted day. Thereafter, the 24 hourly loads of the day are forecasted from the normalized value.

Our proposed generalized algorithm is as follows:

Step 1). If the predicted day / time are belonging to class-1 environment, go to step 4). Otherwise, it is class-2 environment.

Step 2). Construct input information using the input parameters and constraints using any formal or conventional methods like complex algorithm and or identifying redundant constraints before the predicted day or time.

Step 3). Forecast the appropriate parameters.

Step 4). In case that the predicted day or time belongs to a class-1 situation, the value of parameters may vary.

Step 5). Forecast the appropriate parameters with the physical sensitivities calculated in step 4). After taking the above steps, the normalized value of parameters is calculated from the data obtained. Thereafter, the parameters for any class of situation are forecasted from the normalized value.
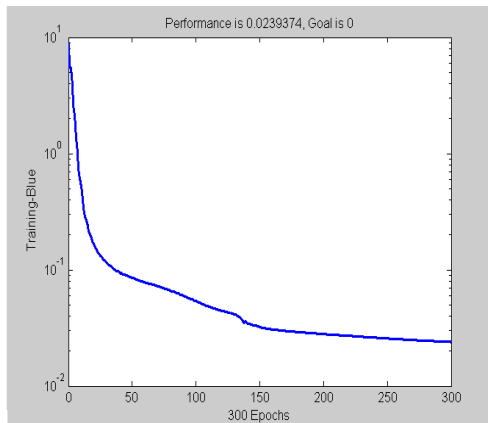

Fig. 2 Result of Back propagation in bounded Variables and Redundant constraints

IV. RESULT AND CONCLUSION

We proposed a hybrid algorithmic structure that improves the accuracy of bounded variables in linear programming problem model by suggesting the training and learning of parameters and constraints. This training is possible in real world application by applying artificial neural network. The above figures shows the results of back propagation in bounded variables and redundant constraints, error rate in linear programming problem model. We believe, the proposed algorithm shows increased performance in accuracy.
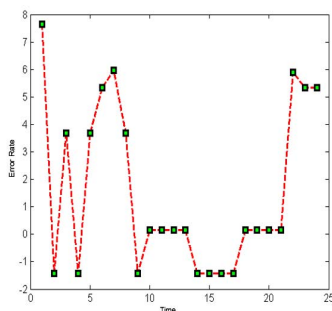

Fig. 3 Error Rate in Linear programming problem model

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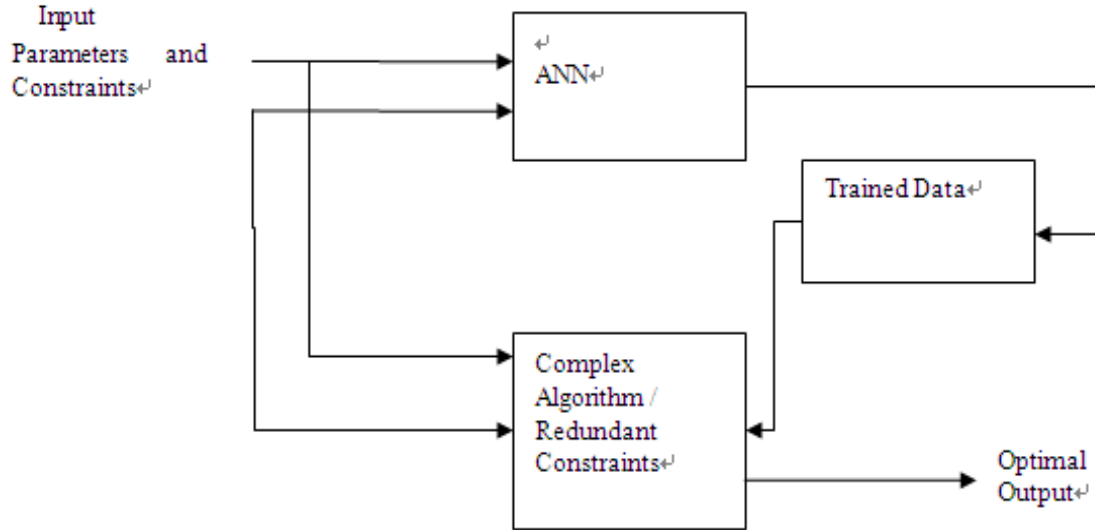
Fig 1. Proposed Hybrid Structure (Where Complex algorithm / redundant constraints is used to achieve optimal in computational effort where as ANN is applied to achieve accuracy in any process model).