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An Efficient Hybrid ModeltoSolve Linear Programming Problems Using Artificial Neural Network

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Abstract—Linear Programming Problems are mathematicalmodels used to represent real life situations.Linear Programming problems arise in real-life economic situationswhere profits are to be maximized or costs to be minimized. Whenformulating an Linear Programming(LP) model, systems analysts and researchersoften 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. Redundantconstraints identification methods are applied for reducingcomputational effort in LP problems. But accuracy of the Linear Programming problems goes down due to this reduction of loops andconstraints. To achieve optimality in accuracy and also incomputational effort, we propose an algorithmic Structure, called Hybrid Model, it trains the constraint and parameterusing artificialneural network beforeapplying the formal methodology.

Keywords: Linear Programming, ANN(Artificial Neural Network), RedundantConstraints, Load Forecasting, Training Parameters.

1. Introduction

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 are mathematical models 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 variable popping 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 [12] 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. In fact, there is a wide literature on thedetection and elimination of redundant constraints in LPmodels [1–11]. Heuristic approach [13] is using an interceptmatrix to identify redundant constraints prior to the start ofthe solution process. In this heuristic approach, tendency ofvariables to pop in and pop out of the basis is eradicated aftereliminating the redundancies. The eradication of pop-in andpop-out substantially reduces the number of iterations.Asignificant reduction in the computational effort is achievedfor LP problems of different sizes in heuristic approach.

2. Related works

Redundant Constraints and Complex Bounded Algorithm

2.1 Complex Algorithm

Very often a linear programming problem may have someor all variables bounded with lower and upper limits inaddition to the given constraints. The lower and upper limitscan represent the minimum and maximum demands forcertain products to solve this kind of these problems a specialkind of technique known as a bounded variable simplexmethod is available. A new algorithm is presented to solvelinear bounded variable problems whose constraintscoefficient is non-negative. In this method the variable arearranged according to their total contribution to the objectivefunction 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

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

If the objective 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 $\alpha_{kj} = B^{-1} Pj$, $K = 1,2, \ldots\ldots, m$

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

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.

2.2. 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

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 $Sk= S$.

3. **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 [14], Kalman filter [15], andknowledge-based expert system [16]. 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 [16]–[24], which are the fuzzy systems andartificial neural networks[19,22,27], have been investigatedin the past decade as an alternative to the conventionalmethods.

3.1 Existing Algorithm

Step 1). 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 2). Construct input information using the load dataduring three days (which are subject to Monday throughFriday) before the predicted day.

Step 3). Forecast the maximum load using the exponentialsmoothing method.

Step 4). 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 5). 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.

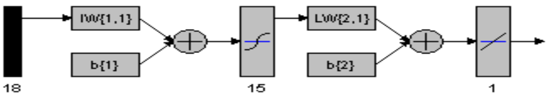

Figure.1 Shows Neural Network for Load Forecasting

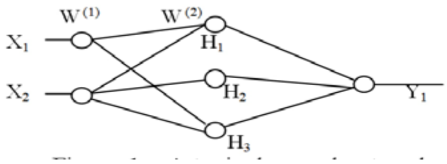

Figure.2Shows a Typical Neural Network

3.2 Our Proposed Algorithm(Structure)

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

Step 2). 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 3). Forecast the appropriate parameters.

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

Step 5). 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.

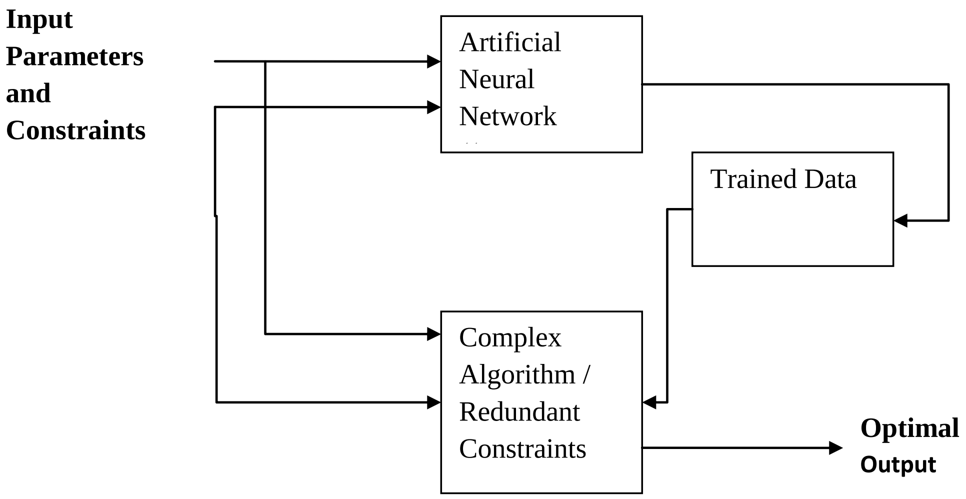

Figure.3 Shows block diagram of the Proposed Method

4. Resultsof the proposed method with training and learning(parameters and constraints) by applying ANN

The proposed a hybrid structure 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. We believe, theproposed hybrid structure shows increased performance in accuracy.

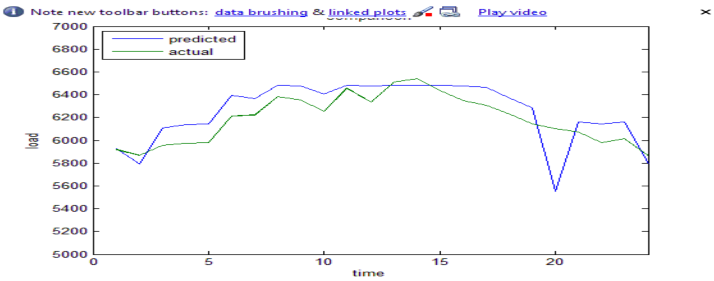

Figure.4 shows the testing phase with trained and learned values for optimization.

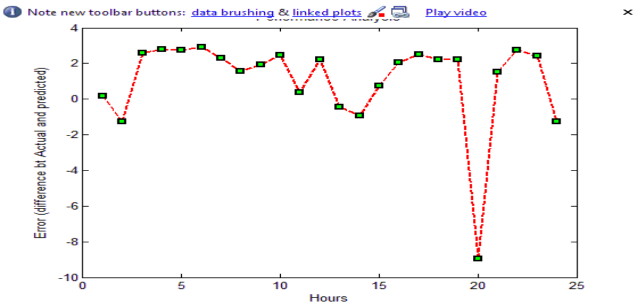

Figure.5 shows error plot difference between actual and predicted values

5. Conclusion

The Hybrid Structure that 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. We 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. 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, we proposed a Hybrid Algorithmic (model) to improve the accuracy of variables in any Linear Programming Problems.

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