Executive Summary

Production systems which are divided into sub-systems constitute multi-level, multi-unit planning systems. The complicated structure of organisations operating with multiple levels of decision making requires effective planning and co-ordinating mechanisms to resolve the conflicting interests/objectives of interested parties within the organisation. The primary objective of this study is to develop and evaluate a prescriptive analytics framework for vaccine allocation in India's supply chain using the GoDEA model. The specific objectives include: align vaccine allocation strategies with the principles of equity, efficiency, and effectiveness, which reflect the organizational mission of optimized multi-level, multi-unit systems - Maximize the overall achievements of the vaccine distribution system at the national level; Optimize the contributions of individual districts/states (DMUs) toward global vaccine distribution targets; Ensure fair and proportionate resource allocation across all districts/states, reflecting their specific needs.

CONTENTS

I. INTRODUCTION

The efficient allocation of vaccines is vital for public health, particularly in a vast and diverse country such as India. With a population exceeding 1.4 billion and significant disparities in healthcare infrastructure, equitable and effective vaccine distribution remains a major challenge. The COVID-19 pandemic highlighted these gaps, as uneven vaccine access and unmet demand were evident in many districts. Despite resource availability, vaccine allocation in India has often relied on subjective judgments and ad-hoc frameworks, neglecting data-driven approaches that could enhance supply chain efficiency and coverage.

Prescriptive analytics offers a solution by combining optimization techniques and decision science to recommend actionable strategies. This project develops a robust supply chain model for vaccine allocation, addressing the shortcomings of subjective decision-making in India's distribution system. Inspired by the Goal Programming and Data Envelopment Analysis (GoDEA) model, the study employs prescriptive analytics to balance objectives such as equitable distribution, minimizing wastage, and optimizing resource allocation. Key metrics like population size, vaccination coverage, healthcare infrastructure, storage capacity, and disease incidence are incorporated to create a data-driven framework for vaccine distribution.

This research fills a critical gap by introducing a scientifically grounded approach to vaccine allocation. The novelty lies in adapting the GoDEA framework to the vaccine supply chain, transforming a subjective process into a transparent, data-driven, and equitable decision-making tool. The proposed model ensures districts receive vaccines based on both need and efficiency, while also establishing a scalable methodology for addressing other resource allocation challenges in healthcare.

II. LITERATUURE REVIEW

Production systems which are divided into sub-systems constitute multi-level, multi-unit planning systems. The complicated structure of organisations operating with multiple levels of decision making requires effective planning and co-ordinating mechanisms to resolve the conflicting interests/objectives of interested parties within the organisation. The following problems were addressed in this paper. Different components (e.g., regions) have diverse goals and priorities, which may not align with those of the central authority. For instance, a region might prioritize industrial expansion, while the central government emphasizes reducing emissions. A single component may face internal trade-offs, such as balancing equity and efficiency in its resource allocation. The central unit must mediate these conflicts to ensure that local decisions contribute to system-wide objectives. Nijkamp et al. [1] advocated the usefulness of multi-objective methods to address planning problems in MULOs. The achievements of conflicting objectives, at the global level , can be compromised using multi-objective programming methods whilst conflicts between the organisational levels of the system require coordinating mechanisms so that all levels act in agreement. Multi-level programming strikes a balance between decentralized decision-making (allowing components to address their unique priorities and

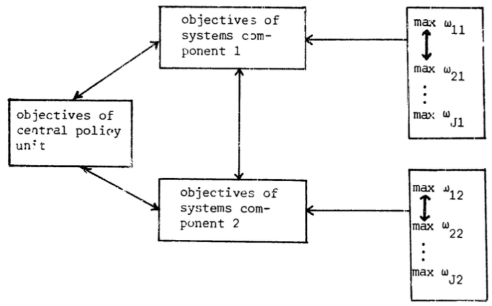

FIG. 1. Multi-dimensional policy framework

objectives) and centralized oversight (ensuring system-wide goals like equity, efficiency, or sustainability are met). This approach helps resolve conflicts between individual and collective objectives, such as when a region's goal for economic growth conflicts with another's environmental priorities.In the paper [1] model formulation is based on multi-objective programming in an iterative process. The center typically provides initial guidelines, constraints, or resource allocations. Components then make decisions based on these inputs and report back outcomes, such as resource requirements or shadow prices (reflecting the value of resources). The center adjusts its coordination strategy iteratively until an optimal balance is reached, ensuring both local and global objectives are satisfied.

According to Anandalingam et al. [2], the most common is the hierarchical form in which a given-level unit (or decision-maker) controls or co-ordinates the units (or decision-makers) on the level below it, and in turn is controlled by the units (or decision-makers) on the level above it. Two cases are modelled, first is decentralized systems [3] [4] [5], where there is one higher-level decision-maker (who is referred to as the centre or leader) and many lower-level decision-makers (who are referred to as divisions or followers), Second is multi-level hierarchy, where there are many levels, with one decision-maker in each level. In each case, Stackelberg behaviour is assumed, whence the centre makes its decision first (i.e. leads) and the divisions react by optimizing their objective functions conditioned on the centre's decision (i.e. followers). On the modelling side, Thanassoulis et al.(1992) [6] provides a sufficient basis for estimating efficient input/output targets for individual DMUs using weighted Data Envelopment Analysis. The DEA models developed by Charnes et al. (1978) [7] base the measure of the relative efficiency of a DMU (decision making unit) on the maximum pro rata adjustment of all its input or alternatively all its output levels that would render it efficient. A DMU is said to be relatively or Pareto efficient if no other DMU or combination of DMUs can improve one of its output levels without at the same time worsening at least one of its other output levels or one of its input levels. The paper [6] addresses more generally the issue of preferred targets for efficiency allowing both input reductions as well as output increases to attain efficiency. The models given in the paper can incorporate preferences over potential improvements to individual input output levels so that the resultant target levels reflect the user's preferences over alternative paths to efficiency. Their formulation is not sufficient, however, to address planning and resource allocation problems where all DMUs of the organisation need to be considered simultaneously. This enhancement would give the opportunity to accommodate global organisational targets, global resource constraints and finally to reinforce

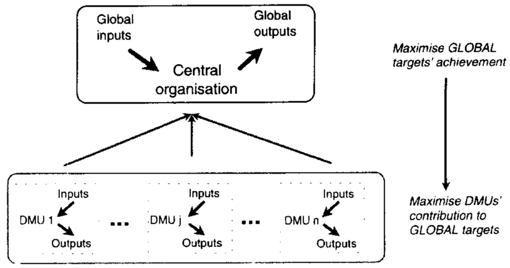

FIG. 2. Centralised Planning System

internal communication between DMUs (resource re-allocation). The development of the planning framework for our target model will embark from the assessment of performance targets for individual DMUs proposed originally by this paper [6].

In the research paper Atanassopoulos et al.(1994) [8] , an interface between Goal Programming and Data Envelopment Analysis (GoDEA) is proposed in order to integrate target setting and resource allocation in MULOs. Centralised resource management is the process, where central management is responsible for the allocation and control of resources allocated to individual decision making units as shown in the figure. The author was a member in the committee formed by the Greek government to perform optimization in the allocation of central grants the local authorities. Resource allocation models, have more demanding structure in the sense that the interactions between individual DMUs need to be taken into account and also the aggregate nature of resources for allocation needs to be encapsulated. GoDEA can be employed for the generation of planning scenarios and also to aid in the negotiation process between different levels of decision making. Thus the existing approaches had the following challenges. Decomposition of large organizations into smaller subsystems, each with its own goals and policies, challenge is to ensure that the decision making process at local level are aligned with the overall organizational goals set by central management(FIG. 2). There are often conflicts between priorities at different levels of organization. Conflicts make it difficult to balance equity, efficiency and effectiveness. The GoDEA method is able to model the trade off between different objectives and co-ordinate the actions of various subsystems to achieve global goals. The GoDEA model also helps set the performance targets for each DMU by comparing its performance with the best practices in system. It ensures that each unit is given realistic but challenging goals that align with global objectives and performance of each DMU is evaluated in terms of how efficiently uses its inputs to produce outputs. The model also optimally allocates resources to ensure that all DMU's have necessary inputs to achieve their targets.

III. OBJECTIVES

The primary objective of this study is to develop and evaluate a prescriptive analytics framework for vaccine allocation in India's supply chain using the GoDEA model. The specific objectives include:

- align vaccine allocation strategies with the principles of equity, efficiency, and effectiveness, which reflect the organizational mission of optimized multi-level, multi-unit systems.

- Maximize the overall achievements of the vaccine distribution system at the national level.
- Optimize the contributions of individual districts (DMUs) toward global vaccine distribution targets.
- Ensure fair and proportionate resource allocation across all districts, reflecting their specific needs.

IV. MODEL AND TECHNIQUES

Goal Programming is used for handling Multiple objectives or Criterias. All objectives are assigned target levels for achievement and a relative priority on achieving these levels. These targets are goals to aspire for and not as absolute constraints. It finds an optimal solution that comes as close possible to the targets in the order of specified priorities. General Goal Programming Model [9]:

$$\text{minimise} : z = \sum_{i=1}^{m} (w_i^+ d_i^+ + w_i^- d_i^-) \tag{1}$$

$$\text{subject to} : \sum_{j=1}^{m} a_{ij} x_j + d_i^- - d_i^+ = b_i;\ \text{for all i} \tag{2}$$

$$n_j, d_i^-, d_i^+ \geq 0;\ \text{for all i and j} \tag{3}$$

(1) represents objective function, (2) and (3) represent the constraints. x_j and b_i are the decision variables and targets respectively, w_i^- and w_i^+ are weights, d_i^- and d_i^+ are negative and positive deviation variables. If weights can be specified then the above formulation reduces to simple linear problem. In reality goals are usually incompatible and some can be achieved only at the expense of other goals.

Now we introduce the Charnes, Cooper, and Rhodes (CCR) (1978, 1979, 1981) [7] ratio of DEA **(M1)**.

$$\text{maximize} : h_o = \frac{\sum_{r=1}^{s} u_r y_{ro}}{\sum_{i=1}^{m} v_i x_{io}} \tag{4}$$

$$\begin{aligned} \text{subject to} : & \frac{\sum_{r=1}^{s} u_r y_{rj}}{\sum_{i=1}^{m} v_i x_{ij}} \leq 1;\ \text{j =1, 2,..., n} \\ & \frac{u_r}{\sum_{i=1}^{m} v_i x_{io}} > \epsilon;\ \text{r =1, 2,..., s} \\ & \frac{v_i}{\sum_{i=1}^{m} v_i x_{io}} > \epsilon;\ \text{i =1, 2,..., n} \\ & \epsilon > 0 \end{aligned} \tag{5}$$

This model is designed to evaluate the relative performance of some DMU, based on observed performance of other DMUs. A DMU is to be regarded as an entity responsible for converting inputs into outputs. The $y_{rj}, x_{ij} > 0$ in the model represent observed amounts of the r^{th} output and the i^{th} input of the j^{th} decision making unit in a collection of j=1,...,n entities which utilize these i=1,...,m inputs and produce these r =1,...,s outputs. One of the j=i,...,n DMUs is singled out for evaluation, placed in the function to be maximized while also leaving it in the constraints. It then follows that DMU's maximum efficiency score will be $h_o 1$ by virtue of the constraints. The $\epsilon > 0$ represents a non-archimedean constant which is smaller than any positive valued real number. In practice, this non-archimedean concept is handled by the DEA computer software used. Hence, it need not be specified explicitly. The value h_o obtained from this ratio satisfies $0 \leq h_o \leq 1$ and can be interpreted as an efficiency rating in which $h_o = 1$ represents full efficiency and $h_o < 1$ means inefficiency is present.

Since the above equation is a linear programming problem , it has a dual which can be represented as:

$$\text{minimize} : \theta - \epsilon \Big[\sum_{i=1}^{m} s_i^- + \sum_{r=1}^{s} s_r^+ \Big] \tag{6}$$

$$\begin{aligned} \text{subject to: } 0 &= \theta x_{io} - \sum_{j=1}^{n} x_{ij} \lambda_j - s_i^- \\ y_{ro} &= \sum_{j=1}^{n} y_{rj} \lambda_j - s_r^+ \\ \lambda_j, s_i^-, s_r^+ &\geq 0 \text{ for i = 1,..., m; r = 1,..., m;} \end{aligned} \tag{7}$$

Note that any admissible choice of λ_j provides an upper limit for the outputs and a lower limit for the inputs of DMUo and against these limits θ is tightened with $\lambda_j, s_i^-, s_r^+ \geq 0$ representing optimizing choices associated with its minimization . The collection of such solutions then provides an upper bound which envelops all of the observations, and hence, leads to the name Data Envelopment Analysis.

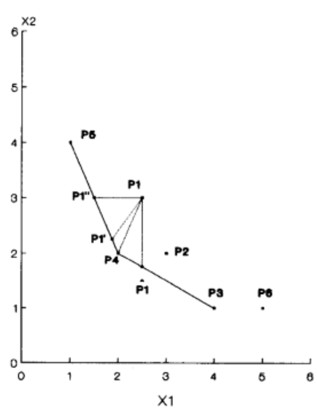

FIG. 3. Two input - One output problem for efficiency

The flexibility of maximization or minimization of preferred input or output is provided in the next model by Thanassoulis et al.(1992) [6]. In setting targets for DMU it would be desirable not only to take account of the nature of the controllability of their inputs and outputs but also of the priorities the attached to improving individual inputs and outputs (**M2**).

$$\max \sum_{r\in R_o} w_r^+\rho_r - \sum_{i\in I_{Do}} w_i^-\sigma_i + \epsilon\Big(\sum_{i\in \bar{I}_{Do}} d_r'^- + \sum_{r\ in\bar{R}_o} d_r'^+\Big) \tag{8}$$

$$\begin{aligned}
\text{subject to}: \ & \sigma_i x_{ij_0} - \sum_{j=1}^{n}\mu_j x_{ij} = 0, i \in I_{D0},\\
& \sum_{j=1}^{n}\mu_j x_{ij} + d_i'^- = x_{ij_0}, i \in I_F,\\
& \sum_{j=1}^{n}\mu_j x_{ij} + d_i'^- = x_{ij_0}, i \in \bar{I}_{D0},\\
& \sum_{j=1}^{n}\mu_j = 1,\\
& \rho_r y_{rj_0} - \sum_{j=1}^{n}\mu_j y_{rj} = 0, r \in R_0,\\
& \sum_{j=1}^{n}\mu_j y_{rj} - d_r'^+ = y_{rj_0}, r \in \bar{R}_0,\\
& \rho_r \geq 1, \forall r \in R_0,\\
& \sigma_i \leq 1, \forall i \in I_{D0}\\
& \mu_j \geq 0, \forall j, d_i'^-, d_r'^+ \geq 0, \forall i and r
\end{aligned} \tag{9}$$

The set of discretionary inputs I_D is partitioned into two exclusive and exhaustive subsets: the subset I_{D0} which consists of the inputs whose levels it is desired should improve within the targets and the subset I'_{D0} which consists of discretionary inputs whose level it is simply desired should not worsen. Similarly for outputs R_0 is the set of outputs we want to increase and R'_0 is the set of outputs which we desire should not worsen [10]. w_r^+ and w_i^- are user-specified weights to be attached respectively to the factor p_r and the proportion σ_i . And $\epsilon << 1$ is a very small positive number, n is the number of DMUs being assessed, y_{rj} and x_{ij} are respectively the r^{th} output and i^{th} input level of DMU$_j$, and m and s are respectively the number of inputs and outputs of the DMUs being assessed. μ_j represents the weight variables assigned to peer DMUs used to form a convex combination. These weights are non negative and help in appropriate comparison of inefficient DMUs to efficient DMUs. The target outputs and inputs yielded by this model for DMU j_0 are

$$\begin{aligned}
\hat{y}^n_{rj_0} &= \rho^*_r y_{rj_0}, r \in R_0,\\
\hat{y}^n_{rj_0} &= y^n_{rj_0} + d'^{+*}_r, r \in \bar{R}_0,\\
\hat{x}^n_{ij_0} &= \sigma^*_0 x_{ij_0}, i \in I_{D0}\\
\hat{x}^n_{ij_0} &= x^n_{ij_0} - d'^{-*}_i, i \in I_F \text{ or } i \in \bar{I}_{D0}
\end{aligned} \tag{10}$$

The dual formulation of the linear model is **(M3)**

$$\begin{aligned}
\text{maximize}:\ & \sum_{r\in\bar{R}_0} \omega_r y_{rj_0} + \sum_{r\in R_0} \omega^0_r y_{rj_0} - \sum_{r\in\bar{I}_0} \phi_i x_{ij_0} - \sum_{r\in I_0} \phi^0_i x_{ij_0} + \sum_{i\in I_0} w^-_i - \sum_{r\in R_0} w^+_r\\
& \sum_{r\in\bar{R}_0} \omega_r y_{rj} + \sum_{r\in R_0} \omega^0_r y_{rj} - \sum_{r\in\bar{I}_0} \phi_i x_{ij} - \sum_{r\in I_0} \phi^0_i x_{ij} \leq 0,\\
& j = 1, .., j_0, ..., n,\\
& \omega^0_r y_{rj_0} \geq w^+_r, r \in R_0\\
& \phi^0_r x_{rj_0} \geq w^-_r, i \in I_0\\
& \phi_i \geq \epsilon, \forall i \in \bar{I}_0, \omega_r \geq \epsilon, \forall r \in \bar{R}_0\\
& \phi^0_i free\ \forall i \in I_0, \omega^0_i free\ \forall i \in R_0
\end{aligned} \tag{11}$$

The phi and omega are weights attached to inputs and outputs and they are the variables in the model. Above formulation can be used to calculate the efficiency scores of weighted inputs and outputs along with division of discretionary and fixed inputs and outputs. In the Figure 3 we can see that according to different weights provided to the two inputs we can achieve any coordinate of efficiency on the efficient curve. Now coming to our target GoDEA model [8](**M4**).

$$\begin{aligned}
\text{minimize}:\ & \sum_{j=1}\sum_{i\in I_c}(P^n_i \frac{n^j_i}{x_{ij}} + P^p_i \frac{p^j_i}{x_{ij}}) + \sum_{j=1}\sum_{r\in O_c}(P^n_r \frac{n^j_r}{y_{rj}} + P^p_r \frac{p^j_r}{y_{ij}}) + \sum_{i\in I_v} P^g_i \frac{d^+_i}{GX_i} + \sum_{r\in O_v} P^g_r \frac{d^-_r}{GY_r}\\
& \text{subject to}\\
& \text{Representation of individual DMUs}:\\
& \sum_{j=1} \delta^k_j y_{rj} - p^k_r + n^k_r = y^k_r, r \in O_c, \forall k\\
& -\sum_{j=1} \delta^k_j x_{ij} + p^k_i - n^k_i = -x^k_i, i \in I_c, \forall k\\
& \sum_{j=1} \delta^k_j y_{rj} \geq y^k_r, r \in O_f, \forall k\\
& -\sum_{j=1} \delta^k_j x_{ij} \geq -x^k_i, i \in I_f, \forall k
\end{aligned} \tag{12}$$

Effectiveness and global targets' achievement:

$$
\begin{aligned}
&-\sum_{j=1} \delta_j^1 x_{ij} - ... - \sum_{j=1} \delta_j^n x_{ij} + d_i^+ = -GX_i, \forall i \in I_v \\
&-\sum_{j=1} \delta_j^1 x_{ij} - ... - \sum_{j=1} \delta_j^n x_{ij} + VX_i = 0, \forall i \in \bar{I}_v \\
&\sum_{j=1} \delta_j^1 y_{rj} + ... + \sum_{j=1} \delta_j^n y_{rj} + d_r^- = GY_r, \forall r \in O_v \\
&\sum_{j=1} \delta_j^1 y_{rj} + ... + \sum_{j=1} \delta_j^n y_{rj} - VY_r = 0, \forall i \in \bar{O}_v
\end{aligned}
\tag{13}
$$

Budget Balance:

$$
\begin{aligned}
&\sum_{i \in I_B} \sum_{j=1} (\delta_j^1 + ... + \delta_j^n) x_{ij} \\
&- \sum_{r \in O_B} \sum_{j=1} (\delta_j^1 + ...\delta_j^n) y_{rj} \leq \text{B} \\
&\forall \in I_B, \forall r \in O_B, \\
&\delta_j^k, n_i^j, n_r^j, p_i^j, p_r^j, d_i, d_r \geq 0, \\
&VX_i, VY_r \geq 0
\end{aligned}
\tag{14}
$$

n_i^j, p_i^j are negative and positive deviation variables for the input i of DMU j

n_r^j, p_r^j are negative and positive deviation variables for the output r of DMU j

d_i^+, d_r^- are negative and positive deviation variables from the global target of input and output

P_i^n, P_i^p preferences over the minimisation of positive/negative goal deviations of input i

P_r^n, P_r^p preferences over the minimisation of positive/negative goal deviations of output r (15)

P_i^g, P_r^g are preference levels related to the global target of input i and output r

GX_i, GX_r input and output global target levels with prior knoledge

VX_i, VX_r input and output global target levels without prior knoledge

B user specified constant for balance between commensurable inputs and ouputs in planning model

I_B, O_B subsets of commensurable inputs and outputs

A simultaneous representation of all DMUs within the planning process of the MULO, is necessary and this has been achieved in the first set of constraints of the planning model (**M4**). The activities of a multi-unit, multi-level organisation can be aggregated and displayed by global levels of inputs/outputs, which are allocated among or produced by individual operating units. The extent to which the organisation achieves these global targets is considered as a surrogate measure of its operational effectiveness which can be supported by the efficient contribution of individual DMUs. This part has been achieved in the second set of constraints. The formulation in model **M4** differs from the target setting in model **M1** insofar as the presence of the goal deviation variables of DMUs are concerned. The allowance given to over and under achieving input/output 'goals' in **M4** has repercussions on the estimated targets of individual DMUs. Thus, suitable formulations of the objective function can yield input augmentation and/or output reduction targets in the light of supporting the achievement of the global organisational targets. The selection of efficient facets, however, is driven by the nature of the objective function, which seeks to facilitate the achievement of global targets. This is a fundamental departure from DEA models which assume that the assessed targets should always contract inputs and expand outputs. The priorities attached to the deviation variables can be used to monitor the contribution of individual DMUs to global organisational targets. The planning process within a MULO is also subject to policy making constraints. As an example, a set of balance of payment constraints are proposed in the third set of constraints for linking the aggregate target achievements of commensurate inputs and outputs. These constraints can be used, for instance, to balance the income-expenses relationship in macroeconomic planning models.

V. APPLICATION OF GODEA TO VACCINE SUPPLY

GoDEA has been envisaged to be used as a decision making tool that would facilitate resource allocation and target setting problems. We collected Vaccines data from various Government websites and reports for input and output variables. The variables were chosen as such that they represented surrogate measures of demand and supply. We collected vaccines allocation, input and output variables data from various Government websites and reports. These include Cowin portal, Sustainable Development Goals report, and Covid-19 Operational Guidelines. The data collected were for 10 weeks starting from 4 - 10 Sep 2021 till 6 - 12 November 2021. The classification of variables representing operational efficiency of a state is given in Table I.

Variables Classification	**Variables**
Controllable Inputs	Cold Storage Equipments
Fixed Inputs	Number of active cases, Logistics Index, Healthcare Workforce, Growth of cases
Controllable Outputs	Total Number of Vaccines
Fixed Outputs	Reduction in cases, Equity distribution score

TABLE I. Classification of Variables

Due to unavailability of each state's wastage data, we included this factor as a constraint in global scenario. Each state's wastage data could be used in the controllable output, and scenario analysis could be performed between Number of vaccines alloted and Wastage according to the trend of growth rate of cases. The Cold Storage equipments is the sum of cold chain points, walk in coolers, walk in freezers, Ice lined refrigerator, deep freezers and solar units. It is critical infrastructure for maintaining vaccine quality. More equipment can store more vaccines safely. The Healthcare workforce is the number of doctors, physicians, nurses per 10,000 people. Its human resource input for administering vaccines; more staff implies higher operational capacity. The number of active cases is the average of the 7 days. Logistics index is a score for all the states given by the government which depends on logistics ease across different states. Better logistics reduce effort per vaccine delivered. Growth gives us the weekly increase in the confirmed cases. Total number of vaccines is the total vaccines administered during a particular week. Reduction in cases imply the total people cured weekly. The Equity distribution score is the total number of vaccines administered till the end of the week divided by total population of that DMU. It measures how fairly vaccines/resources are distributed within the state and supports equity objective. The GoDEA model gives the opportunity for more demanding target setting strategies (Table II), which seek to increase the outputs produced by acquiring extra resources or decrease the inputs used and outputs produced of DMUs. The planning strategy which was used is Output and Input expansion (Table II) and accordingly weights were alloted (Table I). The magnitude of weight alloted to the positive and negative deviations in the output variable was changed to perform sensitivity analysis (for week 24-30 April). The strategy employed was to use the *t* week's vaccine supply of states as controllable output and the total vaccines supplied / administered of *t+1* week as the global output. The model gave results as to what should be the *t+1* week's each state vaccine allocation. Also the reallocation results according to the model were recorded as to how many states need to increase or decrease their outputs for the next week.

Planning Strategy	**Preferences in GoDEA**
Output expansion and input contraction	$\mathrm{P}_i^n, P_r^p \leq 0, P_i^p, P_r^n \geq 0$
Output and input expansion	$\mathrm{P}_i^p, P_r^p \leq 0, P_i^n, P_r^n \geq 0$
Output and input contraction	$\mathrm{P}_i^n, P_r^n \leq 0, P_i^p, P_r^p \geq 0$

TABLE II. Developing planning scenarios

VI. RESULTS

The reallocation result for a particular week is shown in Figure 4. It shows the total vaccines administered in our dataset week, next week and what should be the number of vaccines administered to each state according to the model. According to the model the states which were efficient in all weeks are Uttarakhand, Sikkim, Kerala, Nagaland, Sikkim and Rajasthan.

The trend of total vaccines supplied to to all the states is shown in figure 5, which is evident as the total registration on Cowin website was decreasing with increasing time. At that time the number of cases confirmed had already reached late log phase. Although our strategy was output expansion, the trend of reallocation (figure 6) followed the trend of supply, which shows the model consistency. Whenever there is less supply in the next week, the number of states that should have reduced supply should be more than the number of states with increased supply according to the model to achieve the objective function. The magnitude of difference between them can be controlled through preference variables (figure 8). Results on the achievement of of the global output targets summarise the extent of input/output reallocation among individual DMUs. The goal programming structure of GoDEA leaves open the option of increasing or decreasing the level of inputs/outputs of some of the DMUs irrespective of the global target levels.

The selection of inputs and ouputs to be reallocated is made on the basis of the performance of the corresponding units as compared with their peer efficient local authorities. The reallocation is, undoubtedly affected by the level of global targets and the preferences over their achievement.

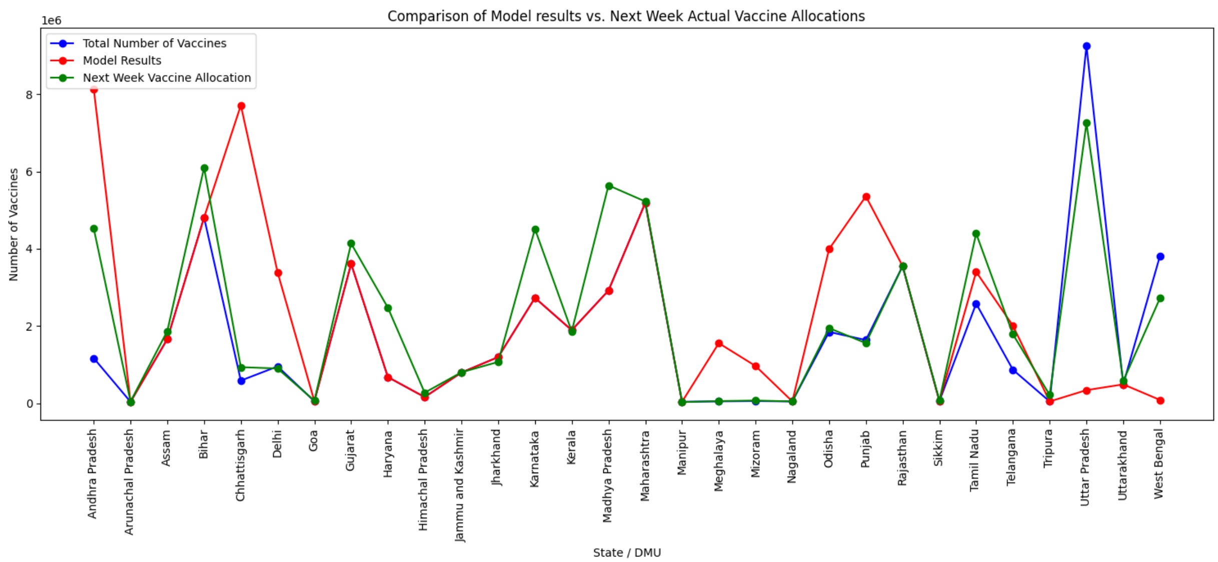

FIG. 4. Comparison line plot

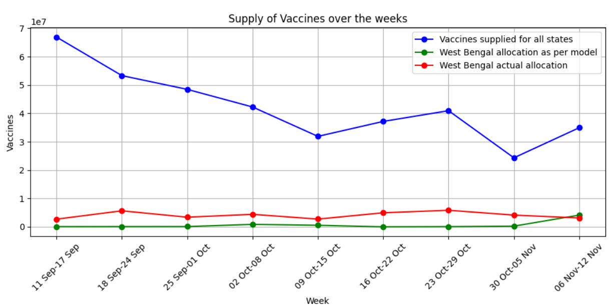

FIG. 5.

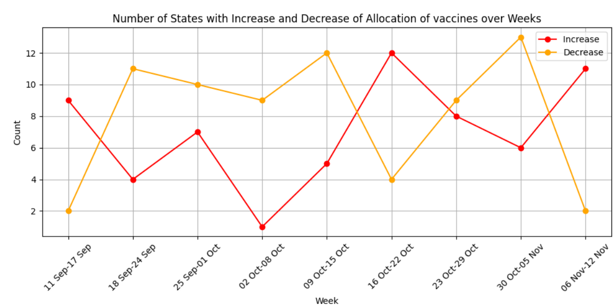

FIG. 6.

There is high sensitivity (figures 7 and 8) in between 0 and 1, as there is high variance in the controllable output and also the nature of the objective function standardises all the deviation variables in a per unit of input/output. Management can use various strategies and magnitude of preference variables to get their desired results. For example, when there is more supply than the demand of vaccines, focus should be made more on minimizing wastage by maximizing cold equipments and minimizing vaccine supply reallocation. Reallocation can lead to huge costs for the central government thus preference variables can be used to determine feasibile targets. GoDEA can be used as a tool of generating alternative planning scenarios.

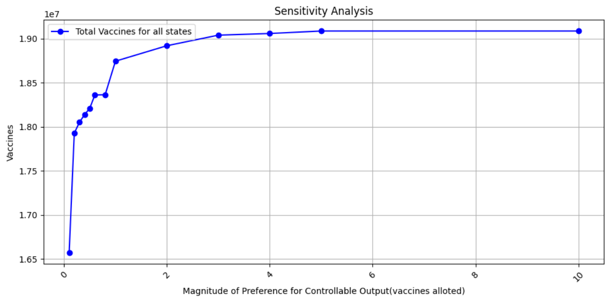

FIG. 7. Comparison line plot

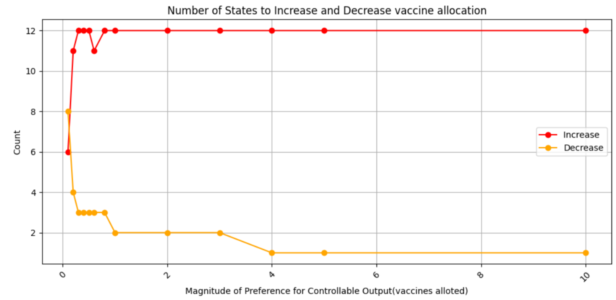

FIG. 8. Comparison line plot

VII. MANAGERIAL IMPLICATIONS

The proposed prescriptive analytics model, based on the GoDEA framework, has broad applicability across various domains beyond healthcare. Multi-unit, multi-level organizations (MULOs) are found in numerous industries and sectors where resource allocation, performance evaluation, and decision-making are critical. This study provides a data-driven approach that managers in diverse fields can adopt to address challenges related to equitable distribution, efficient resource utilization, and effective performance monitoring.

1. Public Sector and Government Agencies: Managers and officials in ministries, public works departments, education boards, and rural development agencies can use the results in resource Allocation such as Optimize the distribution of budgets, grants, or infrastructure investments across multiple administrative units like districts, municipalities, or schools; Performance Monitoring: Track the efficiency and effectiveness of local administrative bodies in achieving government-mandated goals; or Policy Design: Develop equitable and data-driven policies that address disparities in access to resources or services, ensuring alignment with global system objectives.

2. Supply Chain and Logistics: Supply chain managers in manufacturing, retail, and e-commerce industries managing multi-location operations can use the Results in Demand Planning: Allocate inventory or production resources across warehouses or distribution centers to balance demand and minimize costs; or Efficiency Monitoring: Evaluate the performance of individual units in the supply chain (e.g., warehouses or factories) and optimize resource reallocation; or Scalability: Use the model to design scalable solutions for expanding supply chain networks while maintaining efficiency and equity.

3. Corporate Enterprises and Multi-National Corporations (MNCs): Business managers, regional heads, and corporate strategists managing multiple business units or subsidiaries can use the Results for Profit and Resource Optimization: Allocate budgets, personnel, or resources to business units or regions based on their contributions to global corporate targets; Performance Evaluation: Identify underperforming units and recommend efficient strategies or technologies to improve their productivity; or Decision Support: Provide data-driven insights to align individual unit strategies with the corporation's overarching goals of profitability, market share, and growth.

VIII. LIMITATIONS OF THE STUDY

The proposed model has several limitations stemming from its assumptions and real-world challenges. It assumes the availability of accurate and consistent data across DMUs, which is often difficult in resource-constrained environments. The model's reliance on proportional input-output relationships and uniform operational conditions oversimplifies real-world complexities, where non-linear relationships and diverse conditions prevail.

It also assumes stable and clearly defined decision-maker preferences, which may conflict across organizational levels. The reallocation of resources, outputs and weights among DMUs is assumed to be seamless, overlooking logistical, political, or bureaucratic hurdles as well as labour intensive. The static nature of constraints limits adaptability in dynamic environments, and computational complexity can hinder scalability for large systems. Furthermore, the lack of real-time feedback integration reduces its relevance in rapidly changing situations. Despite these limitations, the model provides a valuable and simple framework for optimizing resource allocation and performance evaluation, offering a starting point for addressing equity, efficiency, and effectiveness in multi-level systems.

IX. CONCLUSION

The report gave formulation and application of GoDEA for vaccine reallocation and target setting achieving equity, effieciency, effectiveness. By integrating goal programming and incorporating global targets with specific preferences for input-output deviations, It offers enhanced flexibility and precision in evaluating efficiency. Unlike previous models, GoDEA model [8] allows for the simultaneous optimization of controllable and fixed variables while addressing budget constraints and incorporating domain-specific priorities. A successfull prescriptive analytics framework is formulated for vaccine allocation in a multi-unit, multi-level supply chain using the GoDEA model. More advanced reallocation scenarios can be pursued using GoDEA by allowing reallocation of demand characteristics among different states. It can be implemented as part of a reorganisation plan that would depend on multiple factors such as boundary sharing states. The proposed formulation links the allocation of surrogate measures of inputs and outputs for estimation of targets for individual DMUs, while incorporating decision makers' preferences from different levels of management.

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