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 (DMUs) toward global vaccine distribution targets; Ensure fair and proportionate resource allocation across all districts, 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 multiobjective methods to address planning problems in MULOs. The achievements of conflicting objectives, at the global level , can be compromised using multiobjective 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

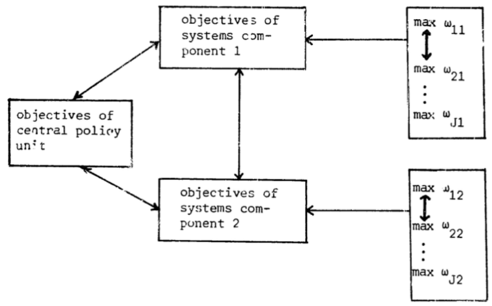

FIG. 1. Multi-dimensional policy framework

priorities and 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 Multiobjective 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 the 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] provide 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 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. This 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

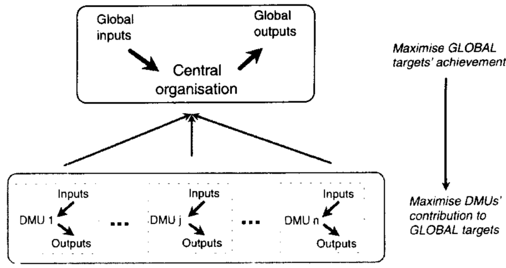

FIG. 2. Centralised Planning System

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) in order to integrate target setting and resource allocation in MULOs. Centralised resource management is considered as the process was 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 government to perform optimization in the allocation of central grants the greek 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 of between different objectives (example efficiency versus equity) and co-ordinate the actions of various subsystems to achieve global goals. Setting performance targets - the GoDEA model helps set the performance targets for each DMU by comparing its performance with the best practices in system. Ensures that each unit is given realistic but challenging goes that a line with Global objectives 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

We have done the formulation of the problem by following the GoDEA model. The procedure is as follows:

- links the allocation of resources with the estimation of performance targets between individual DMUs.
- allows reallocation of resources and outputs among individual DMUs thereby optimizing individual's DMU performances.
- selects efficient technologies for individual DMUs in the light of the satisfaction of the global objectives of the system.
- incorporates decision makers' preferences from different levels of management.

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. Finds and 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, and w_i^- and w_i^+ are weights, and d_i^+ and d_i^+ are negative and positive division variables. If weights can be specified then the above formulation reduces to simply near problem in reality goals are usually incompatible and some goals 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 decision making unit (DMU), designated as DMUs, based on observed performance of j=1,2,..., n 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 are constants which represent observed amounts of the r^{th} output and the i^{th} input of the j^{th} decision making unit which we shall refer to as DMU$_j$ 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 functional 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. We therefore turn to other topics as follow. 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 minimize λ. 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.

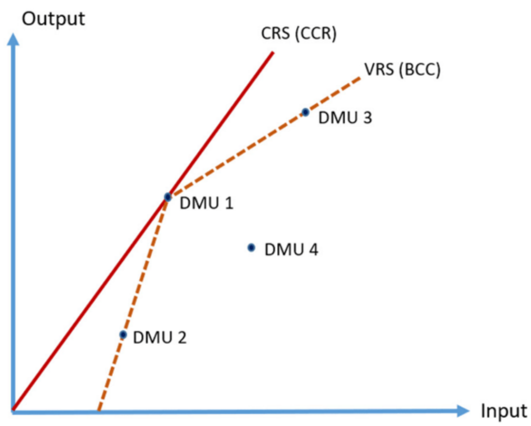

FIG. 3. Pareto curve analysis of Envelope

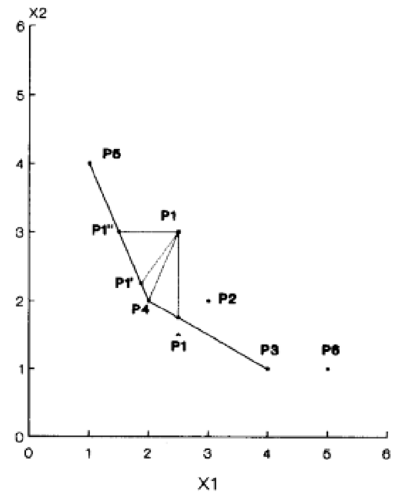

FIG. 4. Two input - One output problem for efficiency

In the Fig 3 we can see that DMU 1, 2, 3 form the envelope. The target allocation for achieving efficiency of the DMU 4 will depend on the weights assigned to the input and outputs. According to the weights assigned it can have any combination of inputs and outputs on the envelope. This flexibility 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 ϵ¡¡ 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 weights variables assigned to peer DMUs used to form a convex combination. These weights are non negative and help in finding the appropriate the comparison of inefficient DMUs to efficient DMUs. The targets yielded by this model for DMU j_0 are

$$
(\hat{y}^n_{rj_0}, r = 1, ..., s; \hat{x}^n_{ij_0}, i = 1, ..., m) \tag{10}
$$

where

$$
\begin{aligned}
\hat{y}^n_{rj_0} &= \rho^*_r y_{rj_0}, r \in R_0, \\
\hat{y}^n_{rj_0} &= y^n_{rj_0} + d_r'^{+*}, r \in \bar{R}_0, \\
\hat{x}^n_{ij_0} &= \sigma^*_0 x_{ij_0}, i \in I_{D0} \\
\hat{x}^n_{ij_0} &= x^n_{ij_0} - d_i'^{-*}, i \in I_F \text{ or } i \in \bar{I}_{D0}
\end{aligned}
\tag{11}
$$

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

$$
\begin{aligned}
\text{maximize}: \; & \sum_{r\in\bar{R}_0}\omega_r y_{rj_0}+\sum_{r\in R_0}\omega_r^0 y_{rj_0}-\sum_{r\in\bar{I}_0}\phi_i x_{ij_0}-\sum_{r\in I_0}\phi_i^0 x_{ij_0}+\sum_{i\in I_0}w_i^- -\sum_{r\in R_0}w_r^+\\
& \sum_{r\in\bar{R}_0}\omega_r y_{rj}+\sum_{r\in R_0}\omega_r^0 y_{rj}-\sum_{r\in\bar{I}_0}\phi_i x_{ij}-\sum_{r\in I_0}\phi_i^0 x_{ij}\le 0,\\
& j=1,..,j_0,...,n,\\
& \omega_r^0 y_{rj_0}\ge w_r^+, r\in R_0\\
& \phi_r^0 x_{rj_0}\ge w_r^-, i\in I_0\\
& \phi_i\ge\epsilon,\forall i\in\bar{I}_0,\omega_r\ge\epsilon,\forall r\in\bar{R}_0\\
& \phi_i^0 free\ \forall i\in I_0,\omega_i^0 free\ \forall i\in R_0
\end{aligned}
\tag{12}
$$

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 4 we can see that according to different weights provided to the two inputs we can achieve any coordinate of efficiency on the efficient curve.

$$
\begin{aligned}
\text{minimize}: \; & \sum_{j=1}\sum_{i\in I_c}(P_i^n\frac{n_i^j}{x_{ij}}+P_i^p\frac{p_i^j}{x_{ij}})+\sum_{j=1}\sum_{r\in O_c}(P_r^n\frac{n_r^j}{y_{rj}}+P_r^p\frac{p_r^j}{y_{ij}})+\sum_{i\in I_v}P_i^g\frac{d_i^+}{GX_i}+\sum_{r\in O_v}P_r^g\frac{d_r^-}{GY_r}\\
& \text{subject to}\\
& \text{Representation of individual DMUs :}\\
& \sum_{j=1}\delta_j^k y_{rj}-p_r^k+n_r^k=y_r^k, r\in O_c,\forall k\\
& -\sum_{j=1}\delta_j^k x_{ij}+p_i^k-n_i^k=-x_i^k, i\in I_c,\forall k\\
& \sum_{j=1}\delta_j^k y_{rj}\ge y_r^k, r\in O_f,\forall k\\
& -\sum_{j=1}\delta_j^k x_{ij}\ge -x_i^k, i\in I_f,\forall k\\
& \text{Effectiveness and global targets' achievement:}\\
& -\sum_{j=1}\delta_j^1 x_{ij}-...-\sum_{j=1}\delta_j^n x_{ij}+d_i^+=-GX_i,\forall i\in I_v\\
& -\sum_{j=1}\delta_j^1 x_{ij}-...-\sum_{j=1}\delta_j^n x_{ij}+VX_i=0,\forall i\in\bar{I}_v\\
& \sum_{j=1}\delta_j^1 y_{rj}+...+\sum_{j=1}\delta_j^n y_{rj}+d_r^-=GY_r,\forall r\in O_v\\
& \sum_{j=1}\delta_j^1 y_{rj}+...+\sum_{j=1}\delta_j^n y_{rj}-VY_r=0,\forall i\in\bar{O}_v
\end{aligned}
\tag{13}
$$

Budget Balance:

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

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 effectivenesswhich can be supported by the efficient contribution of individual DMUs. This part has been achieved in the second set of constraints. 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.

Above models have been applied to different datasets which suit the respective variables in them , to draw out proper conclusions.

V. RESULTS

All the codes have been written in jupyter notebook using the Pulp library. All the models of Goal programming are solved using Linear Programming method. Now we applied the M3M4(equations 13, 14, 15) model to our Vaccine dataset. The selection of efficient facets is driven by the nature of the objective function in M4, which seeks to facilitate the achievement of global targets. This is in contrast with ordinary DEA M2, where a DMU is projected on the facet of the efficient frontier that would minimise the distance between its current performance and the one its should have had it been efficient.

We collected Vaccines data from various Government websites and reports for input and output variables. In some parameters due to unavailability of direct data we used similar variables which will be the best replication. The various government reports and websites used were Cowin portal, Sustainable Development Goals report 2020-2021, Covid-19 Operational Guidelines. The data collected was for the week 24th April 2021 - 20th April 2021 when the Covid-19 growth curve was steep, and is shown in table V. 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. The Healthcare workforce is the number of doctors, physicians, nurses per 10,000 people. The number of active cases and reduction in cases is the average of the 7 days. The equity distribution score is the total number of vaccines administered till the end of the week divided by total population. The planning strategy which was used is Output and Input expansion (Table II)and accordingly weights were alloted (Table I). The weight alloted to the positive deviation in global output variables was kept high for less minimization from required global target levels. Except the the Total number of vaccines all other control global variables of were assumed. The global variable Total number of vaccines used was the number of registrations on Cowin portal for next week.

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

TABLE I. Classification of Variables

The result is shown in V. The graph shows the total vaccines administered in our dataset week, next week and according to the model what should be the number of vaccines administered to each state. The weights assigned to the peer DMUs for attaining efficiency for a efficient DMU is 0 and 1 for itself. But it is 0 for itself for an inefficient DMU and weights whose sum is equal to 1 . According to the model the 10 efficient states were Andhra Pradesh, Arunachal Pradesh, Assam, Himachal Pradesh, Kerala, Maharashtra, Mizoram, Nagaland, Sikkim,West Bengal.

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

State	Cold Storage	Healthcare Workforce	Number of active cases	Logistics Index	Total Number of Vaccines	Reduction in cases	Population	Equity distribution score
Andhra Pradesh	6081	95	94540	3.42	934240	86.95%	5,27,87,000.00	0.168
Arunachal Pradesh	775	22	744	2.77	36478	93.09%	15,33,000.00	0.226
Assam	3044	23	19190	3	517414	88.31%	3,50,43,000.00	0.140
Bihar	3292	17	89863	2.85	651564	71.27%	12,30,83,000.00	0.050
Chhattisgarh	2580	15	121065	3.01	270967	75.58%	2,94,93,000.00	0.087
Delhi	1925	50	95961	3.36	374227	83.75%	2,05,71,000.00	0.173
Goa	180	33	15484	2.78	58425	72.26%	15,59,000.00	0.356
Gujarat	7367	41	120431	3.62	1073598	69.31%	6,97,88,000.00	0.146
Haryana	2668	26	79046	3.37	308278	74.66%	2,94,83,000.00	0.099
Himachal Pradesh	1570	66	14663	2.72	278774	76.18%	73,94,000.00	0.358
Jammu and Kashmir	2566	16	21137	2.87	403772	81.37%	1,34,08,000.00	0.286
Jharkhand	1673	4	49794	2.88	165309	68.74%	3,84,71,000.00	0.041
Karnataka	10155	70	281773	3.37	1087289	72.92%	6,68,45,000.00	0.155
Kerala	5196	115	232785	3.16	736122	78.09%	3,54,89,000.00	0.197
Madhya Pradesh	5719	33	91459	3.21	283267	75.39%	8,45,16,000.00	0.032
Maharashtra	11900	43	684128	3.42	2080998	79.32%	12,44,37,000.00	0.159
Manipur	360	38	928	2.42	76881	93.64%	31,65,000.00	0.231
Meghalaya	644	25	1391	2.56	86888	87.68%	32,88,000.00	0.251
Mizoram	329	50	862	2.31	49452	78.58%	12,16,000.00	0.386
Nagaland	387	1	760	2.28	26838	90.47%	21,92,000.00	0.116
Odisha	4762	39	44983	3.18	319938	84.39%	4,40,33,000.00	0.069
Punjab	2950	56	49839	3.46	570245	78.64%	3,03,39,000.00	0.179
Rajasthan	9434	49	145189	3.16	913097	65.82%	7,92,81,000.00	0.109
Sikkim	235	25	955	2.9	20097	80.97%	6,77,000.00	0.282
Tamil Nadu	8082	65	105680	3.4	662494	85.28%	7,64,02,000.00	0.082
Telangana	3247	10	68831	3.22	939946	78.15%	3,77,25,000.00	0.237
Tripura	571	22	873	2.95	219780	95.26%	40,71,000.00	0.513
Uttar Pradesh	8999	14	297050	3.08	848893	66.46%	23,09,07,000.00	0.035
Uttarakhand	1702	15	39273	2.85	254457	66.49%	1,13,99,000.00	0.212
West Bengal	5445	27	93790	2.99	1145332	80.91%	9,81,25,000.00	0.111

FIG. 5. Dataset

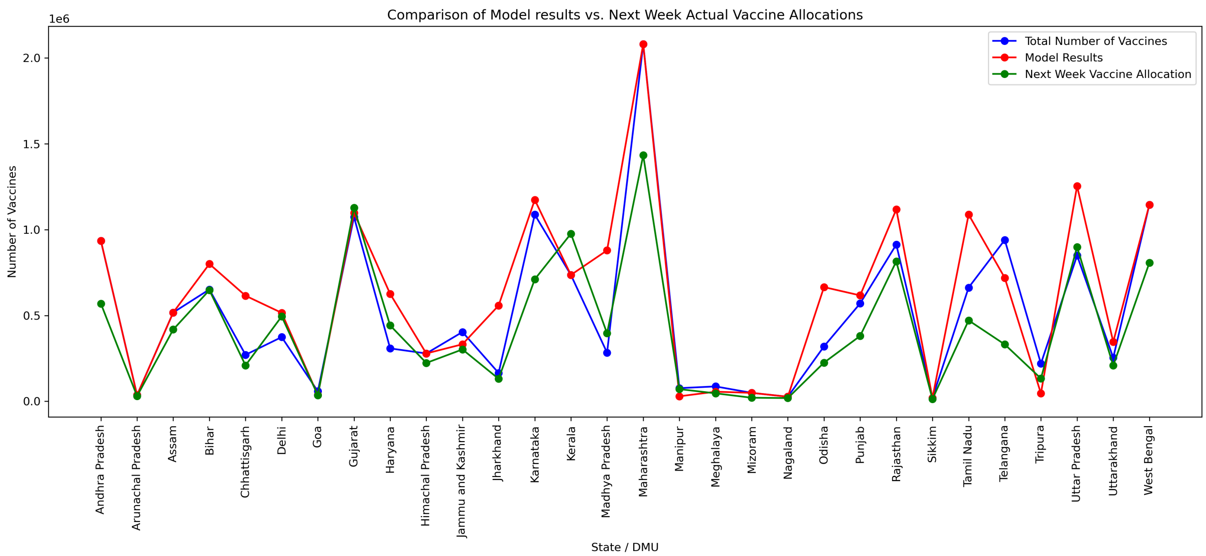

FIG. 6. Comparison line plot

VI. 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.

VII. 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.

VIII. CONCLUSION

The report gave code formulation of both models given in the research paper.While the model by Thanassoulis, E., and Dyson presented in this report represents a significant advancement in the application of Data Envelopment Analysis (DEA). 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, M9 allows for the simultaneous optimization of controllable and fixed variables while addressing budget constraints and incorporating domain-specific priorities. But we also successfully formulated a prescriptive analytics framework for vaccine allocation in a multi-unit, multi-level supply chain using the GoDEA model. Alongside the main GoDEA model, the basic model proposed by Thanassoulis and Dyson was also implemented to serve as a comparative baseline. While the Thanassoulis-Dyson model provided a foundation for evaluating efficiency and resource allocation, it lacked the capability to simultaneously incorporate global objectives, decision-maker preferences, and dynamic resource reallocation. The GoDEA model, by integrating Goal Programming and Data Envelopment Analysis, addressed these limitations effectively. It enabled the linking of resource allocation with performance targets, allowed flexibility in reallocating inputs and outputs, and incorporated preferences from multiple levels of management. The comparative analysis demonstrated that the GoDEA model outperformed the basic model in achieving equity, efficiency, and effectiveness while aligning with global system objectives.

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