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ADAPTIVE ALLOCATION OF REGIONAL BUDGET USING DYNAMIC PROGRAMMING AND GENETIC ALGORITHM

A.E. Abdualiyev, G.K. Sembina
International Information Technologies University, Almaty, Kazakhstan
Corresponding author: dellivine@mail.ru

The optimal regional budget allocation problem is examined in this article, with consideration given to public opinion, strategic priorities, ROI, and long-term sustainability. A mathematical model with two tiers is suggested, with the first tier overseeing the transfer of budget across districts and the second tier managing distribution among sectors within districts. Genetic algorithms (GA) and dynamic programming (DP) are used for optimization.

Data from Kazakhstan' s Almaty region for the years 2022–2024 were used to evaluate the model. Five criteria - utility, inter-district discrepancy, deviation from strategic goals, stability, and computation time were used to conduct a comparative analysis. Although DP achieves the maximum total utility (up to 114.84 conventional units), it also deviates from strategic shares by up to 1.58 and has an inter-district difference of up to 1.25×10^{11} tenge. GA, on the other hand, offers nearly perfect alignment with strategic goals (deviation of 0.03) and 2.5 times smaller disparity, although having lower utility (on average, 4–5% below DP). GA is five times faster than DP, with a constant computation time of 56 seconds.

While DP is appropriate for long-term forecasting scenarios, the acquired results validate the applicability of GA in actual digital public administration situations. The created approach can be applied to participatory budgeting and decision support systems.

Keywords: budget allocation, dynamic programming, genetic algorithm, sectors of activity, strategic goals, participatory budgeting, disparity, optimization.

ДИНАМИКАЛЫҚ БАҒДАРЛАМАЛАУ МЕН ГЕНЕТИКАЛЫҚ АЛГОРИТМ АРҚЫЛЫ АЙМАҚТЫҚ БЮДЖЕТТІ БЕЙІМДІ БӨЛУ

А.Е. Абдуалиев, Г.К. Сембина
Халықаралық Ақпараттық Технологиялар Университеті, Алматы, Қазақстан,
e-mail: dellivine@mail.ru

Бұл мақалада аймақтық бюджетті оңтайлы бөлу мәселесі қарастырылады, мұнда қоғамдық пікір, стратегиялық басымдықтар, инвестицияның қайтарымы (ROI) және ұзақмерзімді тұрақтылық ескерілген. Екі деңгейлі математикалық модель ұсынылған: бірінші деңгейде бюджет аудандар арасында бөлінеді, ал екінші деңгейде - әр аудан ішіндегі қызмет салаларына таратылады. Модельді оңтайландыру үшін динамикалық бағдарламалау (DP) мен генетикалық алгоритмдер (GA) қолданылады.

Модельді бағалау үшін Қазақстанның Алматы облысына қатысты 2022–2024 жылдар аралығындағы нақты деректер пайдаланылды. Салыстырмалы талдау бес критерий бойынша жүргізілді: пайдалық, аудандар арасындағы айырмашылық, стратегиялық мақсаттардан ауытқу, тұрақтылық және есептеу уақыты. DP ең жоғары пайдалыққа (114.84 шартты бірлікке дейін) қол жеткізгенімен, стратегиялық үлестерден ауытқуы 1.58-ге дейін, ал аудандар арасындағы айырмашылық 1.25×10^{11} теңгеге дейін жетті. GA стратегиялық мақсаттарға барынша сәйкес келеді (ауытқу - 0.03) және диспропорцияны 2.5 есе азайтады, дегенмен пайдалығы орта есеппен DP-ден 4-5% төмен. GA-ның есептеу уақыты тұрақты -56 секунд, бұл DP-ден шамамен бес есе жылдам

DP ұзақ мерзімді болжау үшін жарамды болса, GA нақты цифрлық мемлекеттік басқару жағдайларында қолдануға тиімді екендігі дәлелденді. Ұсынылған әдісті партисипаторлық бюджеттеу мен шешім қабылдауды қолдау жүйелерінде пайдалануға болады.

Түйін сөздер: бюджетті бөлу, динамикалық бағдарламалау, генетикалық алгоритм, қызмет салалары, стратегиялық мақсаттар, партисипаторлық бюджеттеу, диспропорция, оңтайландыру.

АДАПТИВНОЕ РАСПРЕДЕЛЕНИЕ РЕГИОНАЛЬНОГО БЮДЖЕТА С ИСПОЛЬЗОВАНИЕМ ДИНАМИЧЕСКОГО ПРОГРАММИРОВАНИЯ И ГЕНЕТИЧЕСКОГО АЛГОРИТМА

А.Е. Абдуалиев✉, Г.К. Сембина

Международный университет информационных технологий, Алматы, Казахстан,
e-mail: dellivine@mail.ru

В статье рассматривается задача оптимального распределения регионального бюджета с учётом общественного мнения, стратегических приоритетов, показателя ROI и долгосрочной устойчивости. Предлагается двухуровневая математическая модель, в которой первый уровень отвечает за распределение бюджета между районами, а второй - за распределение внутри районов по отраслям деятельности. Для оптимизации используются методы генетического алгоритма (GA) и динамического программирования (DP).

Для оценки модели использовались данные по Алматинской области Казахстана за 2022–2024 годы. Сравнительный анализ проведён по пяти критериям: полезность, межрайонная диспропорция, отклонение от стратегических целей, стабильность и время расчёта. Метод DP позволяет достичь максимальной суммарной полезности (до 114.84 условных единиц), но сопровождается отклонением от стратегических долей до 1.58 и межрайонной разницей до 1.25×10^{11} тенге. GA, напротив, обеспечивает почти полное соответствие стратегическим целям (отклонение - 0.03) и в 2.5 раза меньшую диспропорцию, несмотря на несколько меньшую полезность (в среднем на 4-5% ниже, чем у DP). Кроме того, GA стабильно работает в 5 раз быстрее - 56 секунд против 274-299 у DP.

DP подходит для сценариев долгосрочного прогнозирования, тогда как полученные результаты подтверждают применимость GA в условиях цифрового государственного управления. Разработанный подход может быть использован в системах партисипаторного бюджетирования и поддержки принятия решений.

Ключевые слова: распределение бюджета; динамическое программирование; генетический алгоритм; отрасли деятельности; стратегические цели; партисипаторное бюджетирование; диспропорция; оптимизация.

Introduction. Data and optimization algorithms are being used more and more in modern public administration to manage and distribute budgetary resources. At the regional level, when population interests, strategic aims, and economic efficiency must all be taken into account at the same time, this is especially important. Regional budget distribution methods are still dominated by administrative approaches that ignore multi-criteria aspects, even in the face of the advent of digital budgeting alternatives. This raises the possibility of wasteful resource use and escalating social unrest.

The study' s objective is to create and evaluate a two-level model for regional budget distribution that takes into consideration economic efficiency, strategic priorities, and citizen preferences.

Analyzing current methods for budget planning and participatory fund allocation is one of the research' s goals. Another is creating a utility function that takes into account the strategic objectives and opinions of the public.

The work' s importance resides in creating a useful model for digital budget management that can be used to regional planning procedures and broadened to incorporate other elements including social, demographic, and climatic concerns.

Local executive bodies, known as masalikhats, are in charge of managing budget allocation in districts and cities [1,2]. For a five-year term,

the people of different administrative-territorial divisions directly elect the members of Maslikhats, which are district representation bodies. A number of literary materials pertaining to the promotion and receiving of budget funds specifically by Maslikhats were reviewed because the article focuses on the distribution of regional finances within an area.

Nowadays, it is uncommon to see representatives of local executive bodies at frequent maslikhat gatherings. These delegates travel to particular trouble spots to evaluate the state of affairs and examine information gathered for future sessions. The region' s material, cultural, and socioeconomic conditions worsen as a result of these lawmakers'https://doi.org/10.58805/kazutb.v.3.28-1155 careless actions. The public' s lack of faith in government agencies is also a result of the opaque financial allocation process.

The effectiveness of participatory budgeting as a mechanism for citizen participation has been thoroughly examined in the literature [3], since its inception almost thirty years ago. Although there are certain difficulties in putting participatory budgeting into practice, it has a favorable effect on local development [4].

Budgetary resources for cities and districts must be distributed in a way that maximizes the fulfillment of population needs over a wide range of activity areas (AA). One of the most important aspects of budget distribution is the ability for city dwellers to voice their thoughts through voting for priority regions.

The purpose of this research is to create a mathematical model for dynamic district budget allocation using multi-criteria optimization techniques and dynamic programming (DP).

The authors' work in papers [5] and [6], which use non-zero-sum game models and a linear programming model, respectively, is expanded upon in this study.

Materials and methods. To construct the models, official data on budgets, citizen votes, and district priorities of the Almaty region for 2022-2024 were used [7,8].

In total, the following were considered:

- 8 districts: Zhambyl, Kegen, Ili, Karasay, Raiymbek, Talgar, Uyghur, and the city of Kapchagay;

- 7 areas of activity (AA): education, healthcare, transport, infrastructure, digitalization, culture, ecology;

- total budgets by year (scaled to millions of tenge):

- 2022: 181,116.5,

- 2023: 343,168.5,

- 2024: 379,851.2.

Additionally, data on votes and budgets were provided (Tables 1-3):

In line with contemporary methods of sustainable budgeting, a set of criteria (economic, social, and environmental) is employed to guarantee a fair assessment of projects [9]. According to experts, attaining sustainable development necessitates a tight coordination between financial resources and strategic objectives [10].

Table 1 - Voting and budget data for 2022

Districts	Citizens' votes (18 to 50 years old)	District budget (thousand tenge)
Zhambyl	21586	6 814 805
Kegen	3702	4 012 858
Ili	34702,8	154 875 048
Karasay	41904	2 800 000
Raiymbek	3714	4 342 317

Talgar	31176	4 179 912
Uyghur	8073	4 914 391
Kapchagay city	9649	2 677 135

Table 2 - Voting and budget data for 2023

Districts	Citizens' votes (18 to 50 years old)	District budget (thousand tenge)
Zhambyl	21272	13 531 892
Kegen	3468	8 356 368
Ili	34958	241 831 859
Karasay	42704	36 096 011
Raiymbek	3458	6 675 575
Talgar	31735	17 741 840
Uyghur	7791	3 914 441
Kapchagay city	9556	18 520 512

Table 3 - Voting and budget data for 2024

Districts	Citizens' votes (18 to 50 years old)	District budget (thousand tenge)
Zhambyl	20924	21 510 839
Kegen	3299	8 963 667
Ili	29383	259 658 978
Karasay	43485	37 620 311
Raiymbek	3257	4 773 487
Talgar	32015	19 376 414
Uyghur	7511	4 125 466
Kapchagay city	9575	27 22 042

The region's long-term interests are reflected in strategic goals (e.g., enhancing education quality, developing infrastructure, etc.). They serve as each sector' s objective budget share in the model: S_j=[0.20,0.25,0.30,0.10,0.05,0.05,0.05].

ROI (Return on Investment) models are used to compare project expenses and benefits in order to evaluate the return on budget investments [11]. The use of investment payback analysis to support government initiatives and programs is growing [12].

ROI is a measure of the financial return on investments made in each AA, such as digitalization or healthcare. A bigger sectoral contribution to economic growth is indicated by a higher ROI. ROI maximizes the budget' s economic benefits by giving priority to areas with greater financial efficiency: ROI_j=[0.15,0.25,0.35,0.10,0.05,0.05,0.05];

Budget planning should be in line with population well-being and sustainable development goals in the current environment [13]. As

exemplified by Sverdlovsk Oblast, several Russian areas have already amassed distinctive initiative budgeting experience [14].

Model parameters: α = 0.4 – coefficient of the importance of citizens' opinions (votes); β = 0.3 – weight of the penalty for deviation from strategic goals; γ = 0.3 – weight of the importance of ROI (economic return on investment); δ = 0.1 – weight of the penalty for instability (changes compared to the previous year); κ = 0.01 – ROI saturation coefficient (diminishing impact with large investments); λ = 0.2 – coefficient of the penalty for inter-district budget disparity; Δx = 100 million KZT - discretization step in dynamic programming.

At the local community level, optimization techniques like genetic algorithms are already being used to improve management effectiveness [15]. Dynamic programming-based sequential resource allocation techniques allow for the simultaneous optimization of budget spending uniformity and efficiency [16].

The utility function has the form:

$$U_{i.j} = \alpha \cdot w_{i.j} \cdot \ln\left(1 + x_{i.j}\right) - \beta \cdot \left(\frac{x_{i.j}}{B_i} - S_j\right)^2 + \gamma \cdot \frac{ROI_j \cdot x_{i.j}}{1 + \kappa x_{i.j}} - \delta \cdot \left(x_{i.j} - x_{i.j}^{prev}\right)^2 \quad (1)$$

where $U_{i.j}(x_{i.j})$ - total utility from allocating budget $x_{i.j}$ to AA j id i district; $x_{i.j}$ - budget volume (in million tenge) allocated to district i for j-AA; $w_{i.j}$ - normalized share of votes of citizens of district i for j-AA;B_i - total budget allocated to district$x_{i.j}^{prev}$ - budget value $x_{i.j}$ for this AA in last year.

A separate utility function of citizens justifies the participation of the population, the logarithm in the formula models saturation:

$$U_{i.j}^{\ maslikhat} = \alpha \cdot w_{i.j} \cdot \ln\left(1 + x_{i.j}\right) \quad (2)$$

Deviation from strategic goals (in favor of the maslikhat) entails a fine:

$$U_{i.j}^{\ strategy} = -\beta \cdot \left(\frac{x_{i.j}}{B_i} - S_j\right)^2$$

Considering the saturation effect and the declining marginal value, the economic return (ROI) incentivizes investment in efficient AA:

$$U_{i.j}^{\ ROI} = -\gamma \cdot \frac{ROI_j \cdot x_{i.j}}{1 + \kappa x_{i.j}} \quad (3)$$

Significant budgetary adjustments from the prior year are penalized by the sustainability feature:

$$U_{i.j}^{\ temp} = -\delta \cdot \left(x_{i.j} - x_{i.j}^{prev}\right)^2 \quad (4)$$

A penalty for inter-district disparity is also introduced, aimed at reducing imbalances between regions. It minimizes situations where one district receives significantly more or less funding compared to others:

$$Penalty_{region} = -\lambda \cdot \sum_i \left(B_i - \overline{B}\right)^2 \quad (5)$$

The DP model operates as a two-level optimization scheme, where:

1. level 1: Inter-district allocation of the total budget B_i among districts i;

2. level 2: Intra-district allocation of B_i among sectors of activity j.

The global maximum of utility is found using the dynamic programming methodology. The possibility of employing artificial intelligence to improve the effectiveness of budgetary decisions is currently being investigated globally [17]. Geographic information systems and ontological SDSS (Spatial Decision Support Systems) are used to improve the explanation of budget decisions and guarantee equitable inter-regional cash allocation [18].

At both levels, a recursive dynamic programming technique with memoization is used. This optimization technique divides the problem into smaller issues, each of which is resolved iteratively. To prevent doing calculations more than once, each intermediate solution is memorized. Important

characteristics include:

- functions either top-down or bottom-up (top-down in this model);

- uses a caching table to hold values that have already been calculated;

- ensures that the global maximum may be found using a discretized solution space;

- especially good at hierarchical tasks, like the sector of activity level in our model (district level).

For level 2 (intra-district):

The vector$\overrightarrow{x_i} = \{x_{i.j}\}$ is determined, at which:

$$\sum_{j=1}^{M} x_{i.j} = B_i \text{ and max } \sum_{j=1}^{M} U_{i.j}(x_{i.j}) \quad (6)$$

where:

- discretization is used by a step of Δx= 100 million tenge;

- for each subdirection, admissible budgets are sorted out;

- $V\,(j, b_{remain})$is cached - the best utility with a remainder in the j - th AA;

- at the output - the optimal vector $x_{i,j}$.

For level 1 (inter-district) the best utility is with the remainder and the j -th AA.

The objective function looks like this:

$$\max_{\sum B_i = B_i} \quad (7)$$

where:

- recursive optimization is carried out by i-th regions;

- a nested call to the next iteration of the dynamic programming method for each B_i causes optimization by activity areas (level 2);

- state-based memoization is used (i, B_{remain});

- the complexity and execution time of the method depends on the number of iterations and regions.

The study also uses the GA method for budget allocation in order to compare different approaches. It serves as a substitute in this work when the high dimensionality of the dynamic programming approach makes it too slow.

The following steps make up the algorithm:

- encoding of individuals: each individual is a vector $\vec{x} \in R^{N \cdot M}$. The vector is divided into regions, where each region is a subset of the activity areas $x_{i.j}$. Normalization is performed so that $\sum_i \sum_i x_{i.j} = B_i$.

- operators: tournament go selection is carried out (the best of two random ones). Crossover is one-point, between submatrices $x_{i.j}$. The Gaussian mutation $x' = x + \mathrm{N}\,(0, \sigma^2)$with reflection is used as a mutation.

Consequently, the objective function (that the genetic algorithm uses to assess the ”quality” (fitness) of every potential budget allocation choice $\vec{x}$ is known as the fitness function):

$$F\,(\vec{x}) = \sum_{i,j} U_{i.j}\left(x_{i.j}\right) - \lambda \cdot \sum_{i} \left(B_i - \overline{B}\right)^2 \quad (8)$$

Reaching the utility barrier, no improvement during 20 generations, or 200 generations are the terminating criteria.

Results and discussion. The Python language was selected to develop the software, taking into consideration the contents of all required tools and libraries for the job. Tables 5-8 display the models’ findings:

Table 5 - Execution time (in seconds)

Year	DP	GA
2022	274.96	56.00
2023	298.58	56.00
2024	298.89	56.00

Table 6 - Utility

Year	Actual	DP	GA
2022	98.27	114.78	109.24
2023	111.85	114.83	99.81
2024	103.83	114.84	108.57

Table 7 - Inter-district disproportion (tenge)

Year	Actual	DP	GA
2022	4092730961.10	28544519316.54	4124292068.20
2023	14620422792.66	102743987081.38	14806543126.95
2024	17994074137.40	125918918979.22	18092938578.13

Table 8 - Deviation from targets

Year	Actual	DP	GA
2022	0.54	1.57	0.03
2023	0.54	1.58	0.03
2024	0.54	1.58	0.03

The genetic algorithm (GA), which regularly finishes in 56 seconds, is substantially faster than the dynamic programming (DP) technique, which takes between 275 and 299 seconds. This renders DP computationally costly, particularly when considering nested optimization layers and memoization. The high expense of time, however, can serve as an excuse for the caliber of the choices made.

This indicates that, when considering citizen preferences, return on investment, and strategic objectives, DP optimization does, in fact, result in a more advantageous budget allocation. The real distribution, which is linked to administrative budget alignment, offers the least discrepancy. Additionally, GA exhibits a manageable degree of disproportion. Disproportion values in DP, on the other hand, are noticeably greater (particularly in 2023-2024) and are linked to a considerable bias in favor of districts with the highest total utility (e.g. Kapchagay). Genetic algorithms have demonstrated their ability to optimize infrastructure funding allocation, resulting in a more equitable distribution of resources [19].

GA offers the smallest departure from strategy objectives (0.03), which could be a sign of a consistent base or manual modification. Although DP exhibits more notable variations (1.57–1.58) due to its pursuit of global utility maximization at the expense of precise adherence to target proportions, Actual is likewise rather near to the ideal (0.54).

Figures 1–3 show the visual budget distribution:

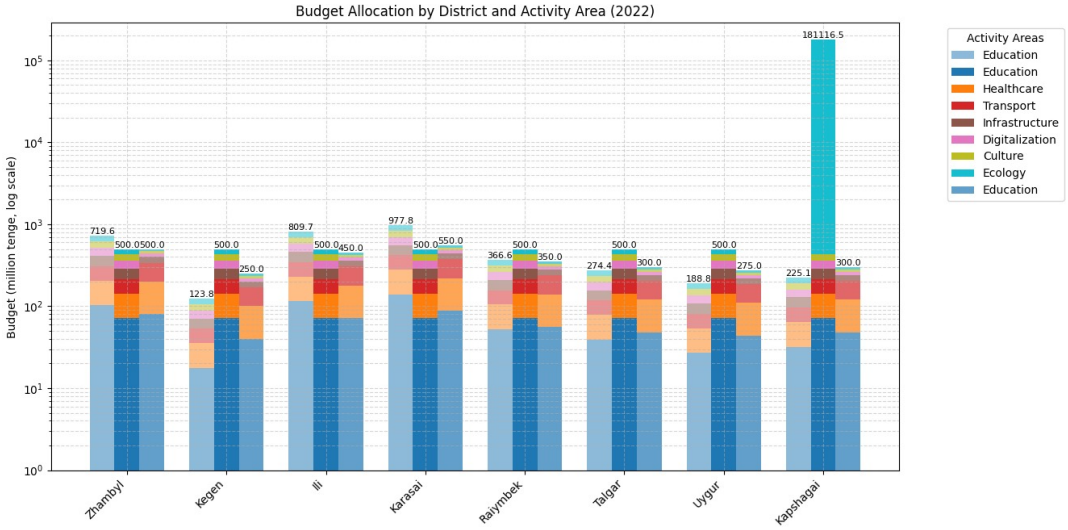


Fig.1 - budget distribution by AA for 2022

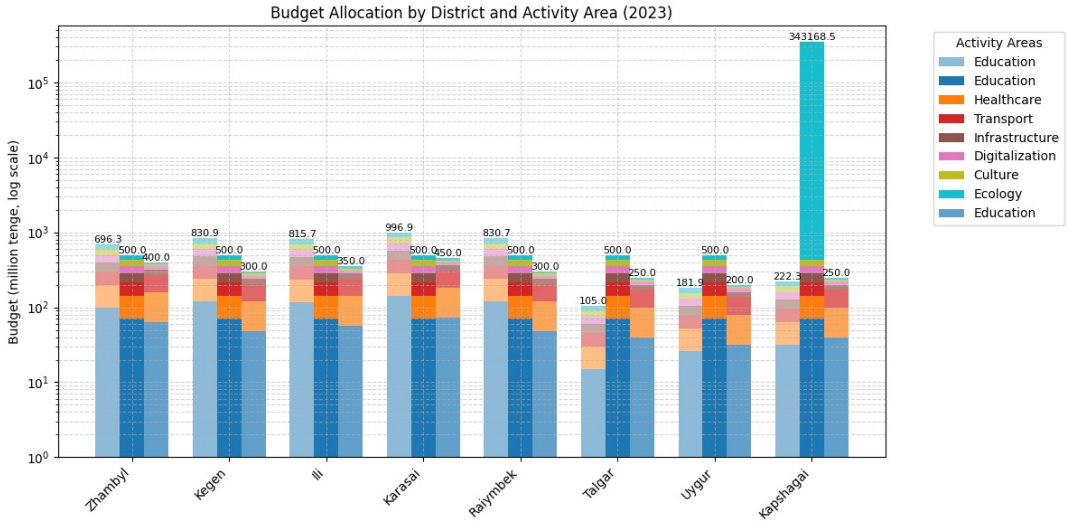


Fig.2 - budget distribution by AA for 2023

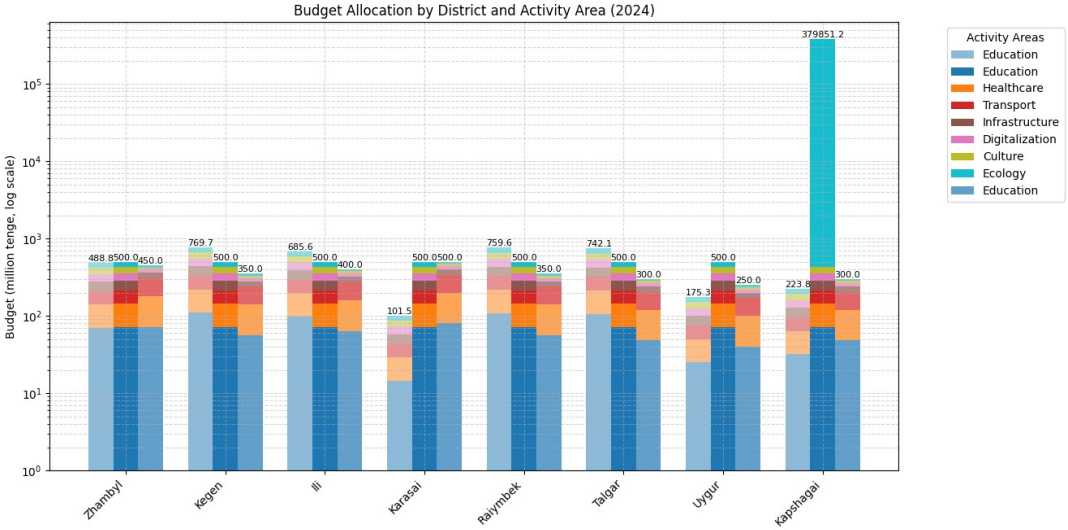


Fig.3 - budget distribution by AA for 2024

Recent studies have also observed that strategic development priorities are frequently not reflected in regional budgets [20]. The statistics demonstrate that there is significant district-to-district variability in the actual distribution. With the exception of Kapchagay, where unusual amounts are found, the DP model allots roughly the same budgets of 500 million tenge to each district annually. These irregularities result from DP' s failure to set a maximum budget per district; instead, the model "pours" everything where the utility function is greatest, particularly in cases where the return on investment is high. This disregards fairness in favor of efficiency. GA avoids extreme values and exhibits balanced behavior, much like the real one.

According to sources, GA frequently offers a more balanced answer than rigorous optimization techniques when analyzing the resulting budget distribution and contrasting the approaches (as in our case: GA reduced the gaps between districts compared to DP).

As a result of the symmetric utility function, it is evident that DP is distributed evenly among districts (by regions), with each area receiving 71.4 million tenge. The distribution is different in GA; more

funds are given to transportation, healthcare, and education, which are closer to the priorities of the populace and return on investment.

A utility function and inter-district disparity analysis is used to compare the two models, as seen in Figure 4:

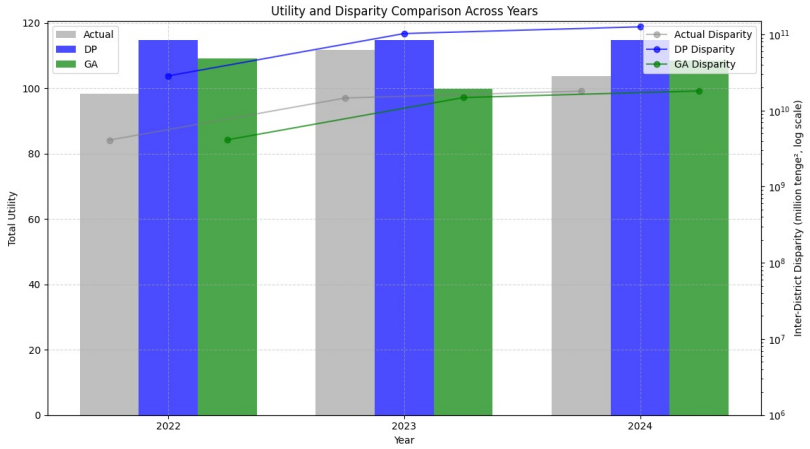


Fig.4 -Comparison graph of utility function and inter-district disparity (on a logarithmic scale) for three budget allocation strategies - Actual, DP and GA (Bars (left axis, Total Utility scale): show the total utility for each strategy in each year. Lines (right axis, Disparity scale on a logarithmic scale): show the level of inter-district disparity for each strategy)

Table 9 - Comparative table of the models' operation

Parameter	Actual	DP	GA
Utility	moderate	high	high
Disproportion	low	high	low
Deviation from strategic goals	moderate	high	minimal
Stability over the years	high	low (racing)	high
Calculation time	-	222–234 sec.	56 sec.
Practical application	exist	requires some improvement	applicable

When it comes to allocating resource limits, comparative research demonstrates that evolutionary algorithms can compete with approximate dynamic programming techniques.

DP exhibits the highest utility (≈114.8) during the course of the three years. This demonstrates how well the dynamic programming approach maximizes overall utility. Although GA performs well, it is marginally less effective than DP. The biggest discrepancy is seen in DP. This will be particularly noticeable in 2023 and 2024. This implies that the algorithm tends to concentrate budgets in specific districts while maximizing utility, disregarding the uniformity criterion. GA maintains a balance between equality and utility by offering moderate disparity.

The conflict between efficiency and justice is seen in the graph: DP has a high efficiency but a high disproportion.

GA is a balance between equality and efficiency. Actual: reasonable disparity, low efficiency. A comparative table of the models' performance by a number of important criteria has been put in place for a more thorough examination of the models'

performance, and it is displayed in Table 9:

Particularly when there are no constraints, the DP model functions effectively as a theoretical maximum. However, only with the addition of further limitations (max/min per district, fairness indicators, etc.) is its practical implementation feasible.

In turn, GA provides a middle ground between social sustainability and efficiency. It may be used with digital budgeting tools, is stable, converges rapidly, and readily adjusts to new objectives.

The necessity to create and apply data-driven decision-making models is highlighted by the fact that the real distribution frequently turns out to be less than ideal and does not match strategic shares, ROI, or public sentiment.

Conclusion. This work focused on developing, implementing, and comparing models of optimal budget allocation between Almaty region districts using two different approaches: genetic algorithms (GA) and dynamic programming (DP). As a baseline for comparison, data on the actual (Actual) allocation of budget funds for 2022, 2023, and 2024 were also utilized. Citizens' votes, strategic objectives, ROI, inter-district equality, and finance inertia were all considered in the model.

In every period under study, the dynamic programming model showed the highest integrated utility values. In 2022, the actual distribution' s generalized utility was 98.3, while GA' s was 109.2. Similar numbers for DP, GA, and Actual in 2023 and 2024 were 114.8 and 114.8, 99.8 and 108.6, and 111.9 and 103.8, respectively. In terms of optimizing the interests of people, maslikhats, and businesses involved in the utility function, these findings show that the DP method performs better than two other strategies. As a result, it guarantees optimal budget utilization.

The dynamic programming approach resulted in a notable rise in inter-district disparity despite the high utility values. In the DP model, there was a significant concentration of resources in some districts, particularly in the city of Kapchagay, where funding in 2022 exceeded 181 thousand million tenge, which is tens of times higher than other values, even though the actual data showed that the budget distribution differences between districts stayed within moderate bounds. This is because DP aims to optimize overall utility by allocating funds to districts with the highest ROI and citizen weights, rather than setting a maximum budget cap per district.

Visually, the figures demonstrate that inter-district disparity (lines on the right axis) rises in tandem with utility (high blue bars). Specifically, under DP, inter-district disparity surpassed 10^{11} tenge in 2023 and 2024, which is 7-10 times greater than in the GA and Actual models. High efficiency is thus attained at the expense of social and regional fairness, which may not be acceptable from the perspective of the state' s balanced development principles.

The distribution' s level of alignment with predetermined strategic objectives, as shown by industry-specific funding shares (education, healthcare, transportation, etc.), received special attention. When it came to reducing deviations from these objectives, the genetic algorithm performed the best; over the course of three years, the deviation was only 0.03 whereas the DP method' s was 1.57–1.58. This is explained by the fact that GA directly incorporates compliance with target shares into the evolutionary selection process, guaranteeing a balance between strategy and ROI, whereas DP just minimizes deviations within its utility function.

Therefore, GA is the best tool when putting government strategies into action rather than just aiming for maximum efficiency is the top goal.

Although DP demonstrated a notable improvement in distribution quality, it came with a high execution time, ranging from 274 to 299 seconds for a single annual calculation. In addition, GA routinely resolved the issue in 56 seconds. GA is a better option when online distribution is necessary or when computational resources are constrained because of the more than five-fold difference. In turn, DP necessitates time and powerful machinery, which are only warranted when creating long-term development scenarios.

An analysis of the final graph comparing the

utility functions and inter-district disparity confirms the above conclusions. All indicators show modest values in the gray columns that represent the real data. Its maximizing character is indicated by the continually increased blue columns (DP). But the lines that show the differences also grow quickly, particularly in 2023–2024. In terms of usefulness, the green columns (GA) are higher than the real ones, but in terms of disparity, they are much lower than DP. This enables us to claim that GA offers the best possible balance between equality and interests. While DP tries to unify the allocation between sectors in order to maximize the overall effect, GA is more responsive to priority sectors, according to a further examination of the budget distribution by areas.

When utility maximization is crucial and there are no stringent constraints on equality or strategic proportions, the dynamic programming approach is warranted. It works particularly well for theoretical modeling and long-term forecasting. The genetic algorithm works best in situations where striking a balance between population interests and strategic objectives is required. It can be used to actual management issues, particularly those where computational efficiency and decision-making speed are crucial.

The outcomes demonstrated the possibility for using optimization models and artificial intelligence to strategic budget planning activities in addition to validating the theoretical tenets. The suggested method can be applied to digital twins of regions and intelligent management systems, and it can be extended to consider other elements, such as climatic, sociological, demographic, and infrastructure.

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Information about the authors

Almaz E.A. - PhD Doctoral Student, Master of Technical Sciences, Senior Lecturer, International University of Information Technology, Almaty, Kazakhstan, e-mail: a.abdualiyev@iitu.edu.kz;

Gulbakyt K. S. - candidate of Technical Sciences, Associate Professor, International University of Information Technology, Almaty, Kazakhstan, e-mail: g.sembina@iitu.edu.kz.

Сведения об авторах

Абдуалиев А. Е.- PhD докторант, магистр технических наук, сеньор-лектор, Университет Информационных Технологий, Алматы, Казахстан, e-mail: a.abdualiyev@iitu.edu.kz;

Сембина Г. К. - кандидат технических наук, ассоц.профессор, Международный Университет Информационных Технологий, Алматы, Казахстан, e-mail: g.sembina@iitu.edu.kz;