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Optimization Strategies in Planned Economy Models: Enhancing Global Profit through Quantitative Forecasting

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Abstract

In this article, we introduce a decentralization algorithm that advances in stages, with the central authority setting quantitative production targets for decentralized units. The decentralized units aim to maximize profits by aligning their production with these targets, incentivized by a bonus system where rewards increase as deviations from the central objectives are minimized. The algorithm's goals include enhancing system efficiency, promoting collaboration through rewards, and enabling adaptive goal setting. The iterative nature of the process allows the central authority to refine its understanding of each unit's technical capabilities, setting more precise production targets over time. The algorithm ensures convergence towards an optimal solution that balances the objectives of both the central authority and the decentralized units. Key results show that the algorithm is monotonic, meaning each iteration progressively moves closer to the optimal solution without regression. This improves decision-making by the central authority as it gains insights into each unit's capabilities. The study also highlights the practicality of the algorithm, showing

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that decentralized units are motivated to adhere to the rules set by the center, leading to a well-coordinated and optimized production system.

1 Introduction

The economy of the 21st century differs drastically from its predecessors. Now, more than ever, new technologies such as Artificial Intelligence and Machine Learning will aid human decision-making by allowing a multitude of parameters to be considered when making judgments. However, when these parameters themselves are changing, for example in the transition from a profit-oriented economy to a planned economy, the predictions made by econometric models become more difficult. A sandbox economy can be created in which parameters may be varied, technological advances might be simulated, and the results appropriately tested against predictions. We propose a spreadsheet economic model that meets these requirements. Cubic growth was observed, with exaggerated dividends in a profit-maximizing world and a dampening effect on profits in a planned economy with centrally-organized production [2]. A brief description of the model is given, presentation of simulation results in a profit-oriented as well as in a planned economy are discussed, and a spreadsheet model can be sourced and run.
The overwhelming dominance of profit-maximizing firms, and the invisible hand of Adam Smith guiding economic activity towards socially desirable ends, has been taken for granted as one of the defining characteristics of a free-market economy. Attempts to end socially undesirable activities on the market itself; for example, creating boards of ethics or a council, have largely been futile. Negative trends often only exacerbate. Analysis of these contrary processes in parallel addressed simple hypothetical criticism with economists and managers arguing about the exclusion of production of vice versus the good of moral stimulant trash-culture and leaving the question unanswered. Expectations of a planned or demand-side economy in which the state or firm might control production, or of the socialization of firms in which power is given into a wider management team or workers' council, would make the situation worse.

2 Theoretical literature

Several studies have delved into the optimization strategies that central planners can employ to align production outputs with global market demands, thereby maximizing profits. For instance, research has highlighted the importance of integrating predictive analytics and advanced forecasting models to anticipate market trends and adjust production plans accordingly [12].
Moreover, contemporary discussions emphasize the role of mixed-integer programming and linear optimization techniques in balancing production targets with resource constraints in a planned economy [7]. These studies underscore the potential for planned economies to achieve global profit maximization by adopting a more data-driven approach to economic planning, moving beyond traditional static models.
Furthermore, the literature also explores the challenges inherent in implementing these strategies, such as the risk of misalignment between central planning objectives and on-the-ground realities, and the potential for inefficiencies arising from overly rigid planning mechanisms [9]. The consensus in recent research is that while quantitative forecasting holds promise for enhancing the effectiveness of planned economies, it requires a flexible and adaptive framework to respond to dynamic global market conditions.
In conclusion, recent studies provide a comprehensive view of how planned economies can evolve by integrating quantitative forecasting tools, but they also caution against the pitfalls of overly deterministic planning models, advocating for a balanced approach that combines predictive analytics with strategic adaptability.
Building on the foundational discussions, recent literature has also delved into the implications of global profit maximization within planned economies, especially in the context of increased economic interdependence and globalization. Researchers like [13] have investigated how planned economies can leverage international trade networks to optimize resource allocation and production schedules, ensuring that goods are produced where they can be made most efficiently while still adhering to centralized economic goals.
Additionally, studies have focused on the integration of artificial intelligence and machine learning into economic planning, proposing that these technologies could revolutionize the ability of central planners to forecast demand and optimize supply chains on a global scale [10]. This literature suggests that by employing sophisticated algorithms and real-time data analytics, planned economies can achieve a level of responsiveness and efficiency that rivals, and in some cases exceeds, that of market economies.

Moreover, recent research has explored the tension between maintaining central control and allowing for localized decision-making, arguing that a hybrid approach-where central goals are set but local units have some autonomy to adjust to specific conditions- might offer the best balance for maximizing global profits while maintaining the core principles of a planned economy [13].
In summary, the latest scholarly contributions underline the potential of quantitative forecasting as a powerful tool for planned economies, particularly when coupled with modern technological advancements. However, they also caution against the over-centralization of decision-making, advocating instead for a more flexible and adaptive model that can respond effectively to both domestic and international market dynamics.

3 Empirical literature

In the planned economy model presented here, the center aims to maximize its overall profit. To achieve this goal, a procedure is implemented where, at each stage, the decentralized units work to both maximize their own profit and meet the target set by the center. Each decentralized unit is equipped with a criterion that reflects the importance assigned to the various objectives and the potential deviations from the target values. This approach is known as "goal-programming by intervals," as described in [1, 4].

4 Proof

Here's a practical example that illustrates the decentralized algorithm described:

a-Deviation: The deviation for each unit can be calculated by: $D_i = |P_i - T_i|$,

where D_i is the deviation of unit i,
P_i is the actual production of unit i,
T_i is the production target set by the central authority for unit i.

b-Bonus: The bonus for each unit is calculated based on the deviation. The bonus decreases as the deviation increases: $B_i = B_{\max} - kD_i$, where B_i is the bonus for unit i, $B_{\max}$ is the maximum bonus,

k is a penalty factor that depends on the importance of minimizing the deviation.

c-Target Adjustment: After each iteration, the target for each unit can be adjusted based on the observed actual capabilities. For example,

$$T_i^{new} = T_i + \alpha(P_i - T_i),$$

where - T_i^{new} is the new production target for unit i,
- α is an adjustment factor $(0 < \alpha < 1)$ that determines the sensitivity of the target adjustments.

d-Iterative Optimization: The objective is to minimize the sum of weighted deviations across all units:

$$min \sum_{1}^{n} w_i D_i,$$

where - w_i is the weight assigned to unit i based on its relative importance,
- n is the total number of units.

e-Convergence: The process is iterative and continues until the deviations are sufficiently small; i.e., if

$$\sum_{1}^{n} D_i < \varepsilon,$$

where ε is a small number representing the convergence criterion.

These formulas allow us to model the algorithm more precisely and see how the targets and bonuses evolve over iterations to reach an optimal solution.

5 Research Methodology

5.1 Global problem

Our economy will be described by the data of K production units, each of them being identified by an index $k = 1, 2, \ldots, K$. For all k, we will denote by $Y_k C R^n$ the possible production set of unit k and by $y_k \in R^n$ the output

of unit k.
We assume that there exists in the economy a price vector $w \in R^n$ in the economy (we will not seek to know how it was fixed).
The problem of the central planning office (CPO) is then the following:
Problem (P):

$$Max \Sigma_{k=1}^{K} < w, y_k > \quad s.c, y_k \in Y_k, \ \forall k = 1, 2, \ldots, K$$

From this moment we will make the following hypothesis:
H1: For all $k = 1, 2, \ldots, K$; the set X_k is convex, compact, non-empty [3].
It is clear that under the hypothesis **H1**, probleby m (P) admits a solution that we will denote $\overline{y} = (\overline{y_k})$, $k = 1, 2, \ldots, K$. To simplify the notations, we set:

$$U(y) = \Sigma_{k=1}^{K} < w, y_k >, and \overline{U} = U(\overline{y})$$

5.2 Decentralization procedure

To know the optimal program $\overline{y}$ the CPO must solve problem (P), however it turned out that in practice the center does not know, or knows in a too approximate way, the production possibilities of each unit k (i.e. sets Y). To try to overcome this difficulty, it is necessary to build procedures, that is to say "rules" for the exchange of information between the center and the periphery, which allow the CPO to have an idea of more precise of the production possibilities of each unit. [8, 11].
In the procedure that we are going to describe now, we will consider two types of information (or rather "prospective clues" and "propositions" to use the terminology of [4, 10]:

- *Prospective indices*: the CPO will propose production targets to each unit.

- *Proposals:*given these production objectives, each unit will send production costs and production plans to the center.

Now, let's see this in detail:
The different steps of the procedure will be indexed by s. Let's go to step s; the CPO knows for all $k = 1, 2, \ldots, K$ an "approximation" Y_k^s of Y_k. It then solves the following problem:

Problem (P^s):

$$\begin{cases} Max\Sigma_{k=1}^{K} < w, y_k > \\ y_k \in Y_k,\ k = 1, 2, \ldots, K \end{cases} \tag{5.1}$$

We put $g^s = (g_k^s),\ k = 1, 2, \ldots, K$ the solutions of this problem and we set:

$$U^s = U(g^s) = \sum_{k=1}^{K} < w, g_k^s >$$

Note: Problem (W^s) indeed admits a solution because we will show later that the set Y_k^s is convex, nonempty, compact. The CPO then sends the production target g_k^s to unit k, two cases can then occur:

- $g_k^s \in Y_k,\ k = 1, 2, \ldots, K$ the procedure is finished because the program g_k^s is optimal (this is easily proved from (i) of Lemma 2 and Theorem 1).
- There exists k such that $g_k^s \in Y_k$ these units then solve the:

  Problem (P_k^s):

$$\begin{cases} Max < w, y_k > +b_k(y_k^+, y_k^-), y_k \in Y_k \\ y_k - y_k^+ + y_k^- = g_k^s,\ y_k^+ \geq 0, y_k^- \geq 0 \end{cases} \tag{5.2}$$

The following hypothesis is necessary for the continuation of our research:
H2: The function $b_k : R_+^n \times R_+^n \longrightarrow R$ is continuous and strictly decreasing with respect to each of these components.
The interpretation of problem (P_k^s) is as follows: The variables y_k^+ and y_k^- represent the deviations (respectively by excess and by default) between the production y_k of the unit and the production target gl set by the center and the function b_k is then interpreted as a "bonus" which is all the more important as the production of the unit is close to the target set by the center (since Ton assumes that the b_k function is decreasing).
Globally, problem (P_k^s) means that unit k is encouraged to maximize its profit $< w, y_k >$ (assuming that all or rather part of it is returned to its various "funds" in an institutional way) while also being encouraged to come as close as possible to the objectives set by the CPO by awarding the bonus b_k. This type of "mixed" incentive corresponds in a simplified manner to the mechanisms that have been attempted to be put in place in the U.S.S.R.in 1970 during the application of the Libermann reform (for more precision one

can consult for example [5, 6].
Let y_k^+, y_k^- and y_k^s be the solutions of problem (P_k^s) and also let μ_k^s be the value of the dual variable associated with the constraint (1) at the optimum. The unit k then sends y_k^s and μ_k^s to the center. Armed with this information, the CPO constructs $Y_k^(s+1)$ from Y_k^s following a method already used in [7, 10, 14].

$$Y_k^(s+1) = Y_k^s \cap H_k^s \tag{5.3}$$

With $H_k^s = f(y) = \{y_k \in R^n \, suchas \, (\tau_k^s, y_k^s) \geq (\tau_k^s, y_k)\}$ Where we put : $\tau_k^s = w + \mu_k^s$.

Knowing $Y_k^(s+1)$ the center can then solve (P^{s+1}) etc...
Finally, to initialize the procedure, we assume that the center has an approximation Y_k^o of Y_k (for all $k = 1, 2, \dots, K$).
H3: $Y_k \subset Y_k^o$, Y_k^o is convex and compact.

6 Discussions and results

The "production" of a planning procedure most often leaves open a certain number of questions relating to the realism of the procedure; that is to say, its ability to describe, in a more or less approximate way, mechanisms that exist or are likely to exist. What about here?
The first point to notice is that the program selected by the center is "unachievable" by the units ("most often" g_s^k will not belong to Y_k i.e. the objectives of the CPO are too high for the units.
The second point, which is incidentally linked to the first, is that throughout this procedure it has been assumed that the units answer "honestly", that is to say that they return y_k^s optimal solution of problem P_k^s but it is clear that in reality a decentralized unit will only adopt this behavior if it has an interest in it. Let's examine this point a little more precisely: suppose that our procedure takes place over two periods ($s = 0$ and $s = 1$). At step $s = 0$ the CPO. Knows Y_k^0 and sends g_s^0, unit k calculates its optimal program (y_s^0, μ_k^0) but sends back to CPO another program (y_k^{*0}, μ_k^{*0}); let us then denote by g_k^1 the objective which would have been calculated from (y_s^0, μ_k^0) and g_k^{*1} that which is calculated from (y_k^{*0}, μ_k^{*0}). At stage $s = 1$, with g_k^1 unit k would have had an income:

$$< w, y_k^1 > + b_k^1$$

and with g_k its income is then:

$$< w, y_k^{*1} > + b_k^{*1}$$

In this simplified framework (since it takes place over two periods), unit k has an interest in not accepting the rules of our procedure if:

$$(< w, y_k^{*1} > + b_k^{*1}) > (< w, y_k^1 > + b_k^1).$$

7 Conclusion

It appears that the interest of the unit in following or not following the rules of the game depends on the relative importance of "profit" compared to "penalization". These two factors act inversely to each other. In this direction, it would be important to define more precisely the "form" that the criterion b_k should take for the unit to have an interest in reporting its actual results. It is known that these concerns are not purely theoretical; on the contrary, they constitute one of the most delicate concrete problems in planning, as noted by [9]. The center often proposes unrealistic objectives ($g_s^k \notin y_k^s$) because it "mistrusts" the units; but, in return, the latter rarely disclose their actual capabilities due to reasons related to both "administrative uncertainty" and the lack of interest (not solely in monetary terms). To address these challenges, several recommendations can be made: enhancing communication channels to build trust and facilitate transparent discussions; setting more realistic objectives by leveraging data and predictive analytics; refining incentive structures to motivate accurate reporting through a mix of financial and non-monetary rewards; implementing administrative reforms to reduce uncertainty and encourage transparency; investing in training and capacity building to help units understand the strategic importance of accurate reporting; and adopting a dynamic system of continuous monitoring and adjustment to fine-tune the balance between profit and penalization. These recommendations, if implemented, could significantly enhance the alignment between the central authority and decentralized units, fostering a more cooperative and efficient planning process.

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