Social Development Paradox: An E-CARGO Perspective on the Formation of the Pareto 80/20 Distribution

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***Abstract*— The Pareto 80/20 principle is extensively cited in discussing social distribution and is usually applied to explain phenomena in economics. However, little in the literature investigates the driving force of such phenomena. The known driving force may help decision makers be proactive in administering a society before it becomes unsustainable. The environments-classes, agents, roles, groups, and objects (E-CARGO) model and the role-based collaboration (RBC) methodology assist the formalization of group role assignment (GRA) problem, which models and solves the optimization problem for a group of agents to play a set of roles from the team's perspective. Based on GRA, this article proposes a new way to investigate social development/distribution problems, such as the Pareto 80/20 principle, with computational social simulations. The proposed method is verified by experiments. This article reveals a social paradox: Emphasizing individual differences inevitably leads to rapid social wealth accumulation and polarization and ignoring such disparities certainly causes slow social wealth accumulation.**

***Index Terms*— Environments-classes, agents, roles, groups, and objects (E-CARGO), group role assignment (GRA), role-based collaboration (RBC), social development, social distribution, the Pareto 80/20 rule.**

Nomenclature

$\mathcal{A}$	Agent set.
$\mathcal{R}$	Role set.
m	Size of the agent set.
n	Size of the role set.
a_i	An element in $\mathcal{A}$.
r_j	An element in $\mathcal{R}$.
$0 \le i, i_0, i_1, \ldots, <m$	Indices of agents.
$0 \le j,\ j_0,\ j_1, \ldots, <n$	Indices of roles.
Q	A qualification matrix.
GRA	Group role assignment.
T	An assignment matrix in GRA.
T^*	Resulted assignment matrix of GRA.
σ^*	Optimal group performance of GRA.
σ^*_{20}	Total Q values of the top 20% assigned agents.
L^e	An agent energy vector (m-dimensional) to inform the relative energy of the corresponding agent.
δ	Role assignment incentive value from the group's perspective.
Z_a	Number of assigned agents with zero Q values.
ε	Maximum deviation of an agent's energy.
ρ	Number of reassignments for the top 20% of agents to contribute 80% of the group performance.

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I. Introduction

The Pareto 80/20 principle [1], [2] states that for many outcomes, roughly 80% of consequences come from 20% of the causes. Other names for this principle are the 80/20 rule, the law of the vital few, or the principle of factor sparsity. This principle is highly cited and applied in discussing economic and social problems, especially in distribution problems, that is, 20% of the people occupy 80% of the wealth. More 80/20 phenomena can be found, e.g., 20% of input produces 80% of output; 20% of people accomplish 80% of the whole work; or 20% of people in a country occupies 80% of the whole wealth of the country.

Recent research states that such an uneven distribution becomes even worse, e.g., 90/10, 50/5, 30/2, or 25/1 [3]. Some argue that the 80/20 rule does not hold for some societies [4]. However, there are few researchers investigating how social development finally creates such a phenomenon, because it seems that such a phenomenon cannot be controlled by humans. It is highly challenging and complex due to the lack of formalization tools.

Thanks to the environments-classes, agents, roles, groups, and objects (E-CARGO) model and the role-based collaboration (RBC) methodology [5], [6] that have been proposed as a well-specified method to investigate complex problems in collaboration and societies (Fig. 1). They are a good fit to model and analyze social problems, which are no doubt complex. This article tries to understand the procedure for a society's development to finally follow the 80/20 rule and how such a phenomenon occurs in the operation of a society.

In this article, we verify that the 80/20 rule states a natural phenomenon, which is not a one-time event but is formed by a continuous operation of a society. Our work explains the reason why the 80/20 rule does not hold for some societies, i.e., the investigated societies have not collected

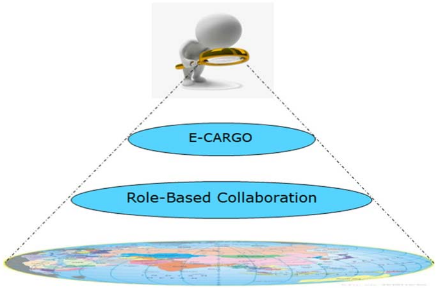

Fig. 1. E-CARGO is a tool to investigate the world.

enough role reassignments, or such societies disappear before the 80/20 rule becomes true [4]. We also reveal the factors that affect the development of the 80/20 distribution. Such factors can be used by administrators of societies or organizations to maintain a healthy social or organizational development.

Through different simulations, we reveal interesting findings including the following.

1) The 80/20 principle is impossible when a society is formed at the beginning.
2) The 80/20 phenomenon is produced by continuously optimized reassignments of roles to the people (agents) in a society.
3) The formation of the 80/20 distribution can be slow or fast due to different incentives. The most important factor in the formation speed of the 80/20 distribution is the individual differences.
4) The 80/20 principle holds because worse distributions make the society unsustainable.
5) This article reveals a social paradox: emphasizing individual differences inevitably leads to rapid social wealth accumulation and polarization and ignoring such disparities certainly causes slow social wealth accumulation.

This article is arranged as follows. Section II specifies the 80/20 rule with GRA [7] by briefly introducing E-CARGO and GRA. Section III states the basic assumptions and the major considerations in the simulation design. Section IV presents the simulation results. Section V discusses the social meanings reflected by the simulation results. Section VI reviews the related work. Section VII concludes this article and points out the potential future work.

II. Group Role Assignment

Simply, GRA is an abstract problem that optimizes the role assignment of a group of agents from the team's perspective. With the help of E-CARGO [5]–[12], GRA can be formally defined as in Definition 1. To understand the major work of this article, we clarify that roles can be taken as entities that express both rights and responsibilities, and the role set is denoted as $\mathcal{R}$; agents are autonomous entities that can play roles, and the agent set is denoted as $\mathcal{A}$; role (agent) assignment is a tuple of an agent and a role, i.e., $\langle a, r\rangle$ $(a \in \mathcal{A}, r \in \mathcal{R})$; $\mathcal{N}$ denotes the set of nonnegative integers, i.e., $\{0, 1, 2, 3, \ldots\}$; $m \in \mathcal{N}(=|\mathcal{A}|)$; $n \in \mathcal{N}(=|\mathcal{R}|)$; $i \in A = \{0, 1, \ldots, m-1\}$ and $j \in R = \{0, 1, \ldots, n-1\}$ are agent and role indices, respectively.

Definition 1 [7]: Given A $(|\mathcal{A}| = m)$, $\mathcal{R}$ $(|\mathcal{R}| = n)$, Q, and L, GRA is to find T to obtain

$$\max \sigma = \sum_{j=0}^{n-1}\sum_{i=0}^{m-1} Q[i, j] \times T[i, j]$$

$$\text{s.t. } T[i, j] \in \{0, 1\}, \quad (i \in A, j \in R) \tag{1}$$

$$\sum_{i=0}^{m-1} T[i, j] = L[j], \quad (j \in R) \tag{2}$$

$$\sum_{j=0}^{n-1} T[i, j] \le 1, \quad (i \in A) \tag{3}$$

where Q is the qualification matrix that expresses the suitability of an agent for a role, i.e., $Q[i,\ j] \in [0, 1]$; T is an assignment matrix, i.e., $T[i,\ j] = 1$ means that agent i is assigned to role j and $T[i,\ j] = 0$ means the opposite; and L is a vector that represents the numbers of agents required for each role, i.e., $L[j] \in \mathcal{N}$. Constraint (1) informs that role i can be assigned agent j or not; (2) means that role j is workable; and (3) indicates that each agent is assigned at most one role.

Definitions 2–4 are used to formally define the top 20% assigned agents so as to define the top 20% agents' contribution or wealth distribution.

Definition 2: The ordered assigned Q value vector by assignment matrix T, denoted as $Q^O(T)$, is a $\sum_{j=0}^{n-1} L[j]$–dimensional vector, where $\forall(0 \le i_1, i_2 < \sum_{j=0}^{n-1} L[j])\ \exists(0 \le j_1 \ne j_2, j_1, j_2 < n)(T[i_1, j_1] \times T[i_2, j_2] = 1), (i_1 < i_2)) \to (Q^O(T)[i_1] \ge Q^O(T)[i_2])$.

Definition 3: The ordered top 20% assigned Q value vector by assignment matrix T, denoted as $Q^{O20\%}(T)$ is an $\lfloor m \times 20\%\rfloor$– dimensional vector, where $Q^{O20\%}(T)[i] = Q^O(T)[i](i \le \lfloor m \times 20\%\rfloor)$.

Definition 4: The top 20% assigned agent index set by assignment matrix T, denoted as $A^{20\%}(T) \subset A$, is defined as all the agent indices that have a Q value in $Q^{O20\%}(T)$, i.e., $\forall i \in A^{20\%}(T)(\exists j \in R, Q[i, j] \in Q^{O20\%}(T), T[i][j] = 1)$.

For example, if $m = 150$ and $\sum_{j=0}^{n-1} L[j] = m$, the top 20% agents, i.e., $A^{20\%}(T^*)$ means the top 30 assigned agents with the first 30 highest assigned Q values.

We use T^* to express the assignment matrix obtained by Definition 1, and $\sigma^* = \sum_{i=0}^{m-1}\sum_{j=0}^{n-1} Q[i, j] \times T^*[i, j]$. We use $\sigma^*_{20} = \sum_{i \in A^{20\%}(T^*)}\sum_{j=0}^{n-1} Q[i, j] \times T^*[i, j]$ to express the contribution or wealth distribution of the top 20% agents.

Note that the social meanings of the Q matrix can be various, e.g., the qualifications or the competencies of an agent on a role. Such qualifications or competencies can be translated to the ability to contribute or acquire wealth. According to the principle of "working more and getting more," the qualification values can also be explained as the individual gains out of the group's outcome. Therefore, the social meaning of σ can be the whole investment/input or the whole production/output of a society.

With the help of GRA, we may formally define the 80/20 rule. With such formalization, we can provide an exact result that might be applied in decision making.

Definition 5: The Pareto 80/20 rule in GRA is that the top 20% assigned agents' performance is about 80% of the team performance. That is, $\sigma^*_{20} \approx \sigma^* \times 80\%$.

We need to emphasize that under the assumption of GRA, the 80/20 rule is not true at the beginning. It is impossible to make this rule work for an initially formed group because one agent contributes at most 1.0 to the group performance σ. With our initial experiments on 100 random GRA cases, $m = 150$, $n = 10$, $Q[i, j] \in [0, 1]$ are evenly distributed random numbers, and $L[j] = 15$ $(j \in R)$, the maximum (Max), average (Ave), and minimum (Min) rate of the top 20% (30 in this case) agents' contributions is 22%, 21.79%, and 21%, respectively. We can state a theorem as follows.

Theorem 1: Suppose that the Q values are random numbers evenly distributed among agents and roles and $m = \sum_{j=0}^{n-1} L[j]$. The Pareto 80/20 rule is not true for GRA in the sense of group performance.

Proof: $m = \sum_{j=0}^{n-1} L[j]$. There are two extreme cases: 1) $n = m$ and $L[j] = 1 (j \in R)$ and 2) $n = 1$ and $L[0] = m$.

For 1), the values of $1/m$, $2/m, \ldots,$ and 1 are evenly and randomly scattered among m agents for each role in Q.

$\because$ GRA is to find an optimized T^* matrix.

$\therefore \sigma^* = m$ and $\sigma^*_{20} = m\times$ 20%, and $\sigma^*_{20}/\sigma^* = 20\%$.

For 2), the values of $1/m$, $2/m, \ldots,$ and 1 are evenly and randomly scattered among m agents in an $m\times$ 1 matrix Q.

$$
\begin{aligned}
\because \sigma^* &= 1 + (m-1)/m + (m-2)/m + \cdots + 1/m \\
&= (m+1)/2 \text{ and} \\
\sigma^*_{20} &= [1 + (m-1)/m + (m-2)/m + \cdots \\
&\quad + (m - \lfloor m \times 20\% \rfloor + 1)]/m \\
&= 0.2m \times (1.8m+1)/(2m) = 0.1 \times (1.8m+1) \\
\therefore \sigma^*_{20}/\sigma^* &= 0.2 \times (1.8m+1)/(m+1) \le \lim_{m\to\infty} 0.2 \\
&\quad \times (1.8m+1)/(m+1) = 0.36. \\
\therefore \sigma^*_{20}/\sigma^* &\in (0.2, 0.36). \\
&\therefore \text{The 80/20 distribution is impossible.}
\end{aligned}
$$

Theorem 1 is proven. ■

Evidently, the initial experiments support the estimation in the proof of Theorem 1.

III. Simulation Assumptions and Design

A. Assumptions

Theorem 1 means that in a society it is impossible for 20% of people to contribute 80% of the society's output. That is, any society at the beginning does not support the 80/20 rule. Then, we may conjecture that the 80/20 phenomenon happens after a long-term operation. Such a long-term operation involves a series of social activities. We use the reassignment of roles plus the change of agent qualifications to express the social activities. We can also use the group performance, i.e., σ^*, as the result or output of these social activities. The individual performance is expressed by the qualification values of agents on the assigned roles. From GRA, we can think of other factors that affect the contributions of agents to a team.

The simulations are based on the following assumptions.

1) The number of agents in a society does not change. This is reasonable because a tiny partial replacement (leaving and joining) can be ignored. For example, Association for Computing Machinery (ACM) [https://www.acm.org/] has members about 100 000 for many years and IEEE Systems, Man, and Cybernetics SMC) Society [https://ieeesmc.org/] has members between 4000 and 5000 for many years.
2) This society is organized by optimizing the whole performance. That is, the administrators or board of governors (BOG) of society encourage the optimizations of GRA. Note that, in a society, the administrators may not have the GRA optimization tool, but they try to maximize the whole performance with their conventional ways, e.g., humanistic, psychological, and social, and most of the cases, they believe that their decisions are optimized.
3) Agents are different [13], [14]. The differences may be of ability or energy.
4) The qualification (Q) values of agents are changing based on individual differences.

The above assumptions are rational because each has corresponding social facts. Therefore, we can confirm that the simulations based on these assumptions are acceptable.

B. Design

In the simulations, we hope to find hints in the following aspects: 1) setting pertinent parameters for the energy levels; 2) find an appropriate method to compute individual contribution to (distribution from) the team; and 3) find the method to collect the individual contributions of the 20% part.

In Simulations 1–6, the qualification values of agents on roles will be randomly created initially and updated by

$$
Q[i, j](t+1) = \begin{cases} Q[i, j](t) \times (1 + L^e[i]) \times \delta, & (T[i, j](t) = 1) \\ Q[i, j](t) \times (1 + L^e[i]), & (T[i, j](t) = 0) \end{cases} \quad (i \in A,\ j \in R) \tag{4}
$$

where $t = 0, 1, \ldots, k$ to mean the tth reassignment and $Q(0)$ means the initial Q. The meanings of this setting include the following.

1) The Q values change according to the agents' energy value, i.e., $\times(1 + L^e[i])$, which means that more efforts increase qualifications and has a similar meaning to that of the compound interests of banks.
2) The Q values on the assigned roles change more than unassigned roles, i.e., $\times\delta$, which is a social factor in tuning the qualification values for the assigned agents; and other than the initial Q, an individual Q value (i.e., $Q[i, j](t)(t > 0)$) in the updated Q matrix can be more than 1 due to the energy and persistence during reassignments.

In (4), we introduce an energy value for agents. $L^e[i] \in [-\varepsilon, \varepsilon]$ means the relative energy value of agent i $(i \in A)$ to reflect that agents are different. We use ε to express the largest energy deviation from average (e.g., 1) for individual

TABLE I
SIMULATION 1: ONE RANDOM GROUP

Re-Assignment	σ^*	σ^*_{20}	σ^*_{20} / σ^*
0	106.84	29.16	0.27
1	112.76	48.94	0.43
2	164.67	92.63	0.56
3	272.89	177.92	0.65
4	482.49	347.71	0.72
5	886.27	687.63	0.78
6	**1669.84**	**1368.71**	**0.82**

agents. For example, suppose that ordinary people work 8 h a day ($L^e[i] = 0$), some diligent people may work 16 h a day ($L^e[i] = 1$), but others may work only 2 h a day ($L^e[i] = -0.75$). We believe that $\varepsilon \in [0, 1]$, because a person working more than 16 h may not be sustainable.

IV. SIMULATION DESIGN AND EXPERIMENTS

A. Simulation 1

In this simulation, $Q[i, j](0) \in [0, 1]$ ($i \in A$, $j \in R$) and follows the uniform distribution, i.e., $U(0, 1)$. A random example in Table I shows that after the sixth reassignment, 20% of the team members contribute more than 80% of the team performance. In this simulation, we use $m = 156$, $n = 4$, $L = \{1, 5, 25, 125\}$, $\sum_{j=0}^{3} L[j] = m = 156$, $L^e \in [-1, 1](j \in \mathcal{R})$, and $\delta = 1.1$. The meanings of this simulation include the following.

1) The team is composed of the maximum number (the Dunbar number [15]) for people to handle in their social networks.
2) The positions are hierarchically organized and each higher rank agent manages 5 at the lower rank (The magic number in psychology, i.e., 7+/−2 [16]. Note that this factor is only used for setting L but not used for assignment.).
3) The agents' energy values are evenly distributed from very lazy, i.e., −1, to very energetic, i.e., 1.
4) There is one incentive factor expressed by δ to express the encouragement of taking roles.

Table I presents the development of the distributions changing from 27/20 to 82/20. To simplify descriptions, we denote ρ as the reassignment times for the top 20% of agents to contribute ≥80% of the group performance. That is, if $\rho = 8$, we mean that after the eighth reassignment, the 80/20 distribution occurs. We test 100 random cases (Fig. 2). The maximum, average, and minimum ρs are 10, 6, and 5, respectively.

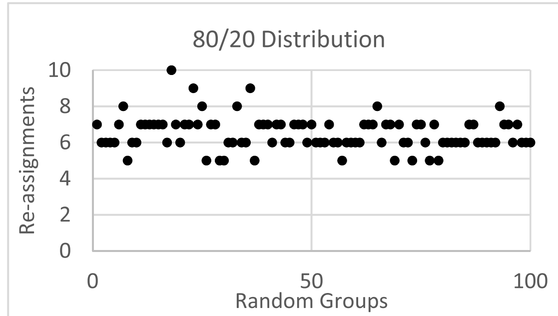

Fig. 2. Simulation 1: Reassignments for 80/20 distribution.

TABLE II
SIMULATION 2: ONE RANDOM GROUP

Re-Assignment	σ^*	σ^*_{20}	σ^*_{20} / σ^*
0	103.91	29.47	0.28
1	112.62	38.07	0.34
2	133.17	55.28	0.42
3	167.61	82.35	0.49
4	220.42	122.65	0.56
5	298.98	183.61	0.61
6	415.19	276.39	0.67
7	586.94	417.43	0.71
8	841.34	631.16	0.75
9	1219.33	956.07	0.78
10	**1782.78**	**1449.60**	**0.81**

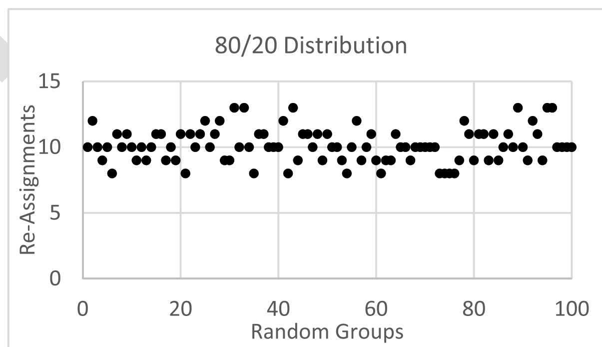

Fig. 3. Simulation 2: Reassignments for 80/20 distribution.

B. Simulation 2

Now, let us check the impact of individual (L^e) and collective (δ) factors. We conduct another simulation by setting $L^e[i] \in [-0.5, 0.5](i \in A)$ and $\delta = 1.05$ and keeping others the same as those in Simulation 1. Table II presents the development of the distributions changing from 28/20 to 81/20 in Simulation 2.

We also try 100 random cases (Fig. 3). The ρ is 13, 10, and 8 for the maximum, average, and minimum, respectively.

C. Simulation 3

In this simulation, we keep all the settings in Simulation 1, but only change the number of $m > \sum_{j=0}^{3} L[j] = 156$. We change m from $156 + 16(=156 \times 10\%) = 172$, with a step of 16, to 316. We compress the data into three figures (Figs. 4–6), the maximum, average, and minimum ρs. The top right legends mean the range of $L^e[i]$ ($i \in \mathcal{A}$).

Form Figs. 4–6, we notice that the higher the L^e values, the faster for a group to obtain the 80/20 distribution. The more agents that have no assigned roles, the faster for a group to approach 80/20. However, the impact degree of the L^e values is much more evident than the number of idle agents.

D. Simulation 4

Following Simulation 3, we set evenly distributed $L^e[i] \in [-0.5, 0.5](i \in A)$ and change δ from 1.05 to 1.10 with a step of 0.01 for different ms from 172 to 316 with a step of 16. It is interesting to conclude that the factor δ does not affect notably the ρs. Table III shows two sets of the collected data.

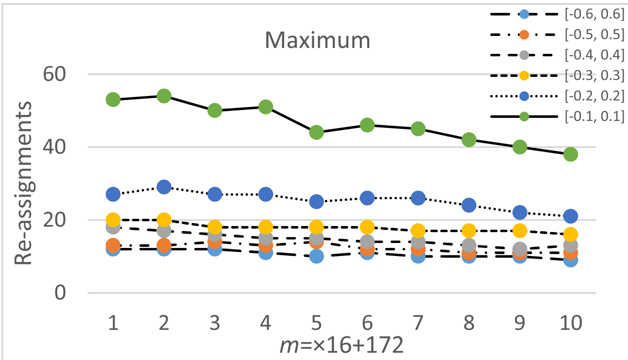

Fig. 4. Simulation 3: Maximum ρs.

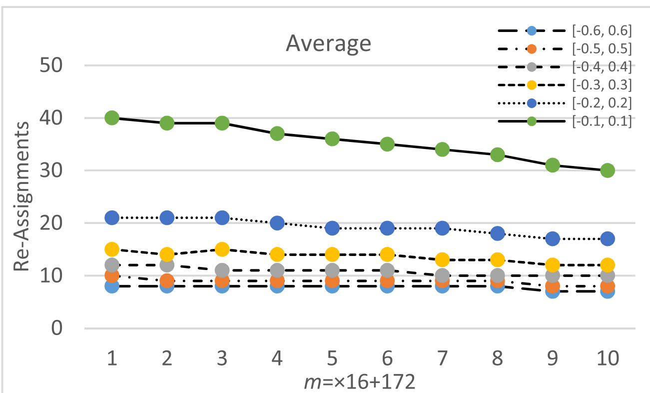

Fig. 5. Simulation 3: Average ρs.

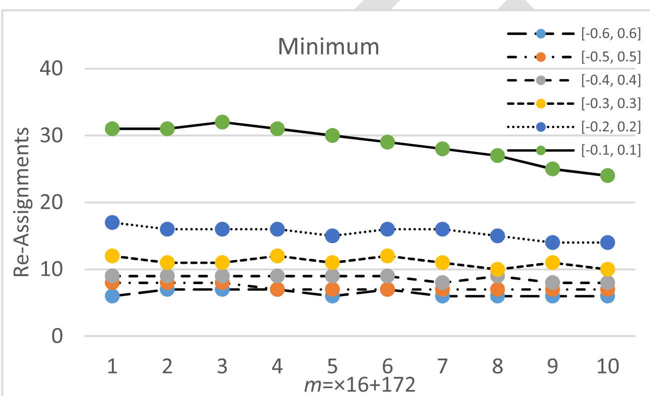

Fig. 6. Simulation 3: Minimum ρs.

E. Simulation 5

In the simulation, we use $Q[i, j](0) \in [0.5, 1]$ to mean that all the agents are initially well qualified for every role in the group. We use the same settings as those in Simulation 3. Table IV expresses the results for $\delta = 1.05$ and $L^e[i] \in [-0.5, 0.5]$ $(i \in A)$.

Compared with the case for $Q[i, j](0) \in [0, 1]$ simulations in Simulation 3, there are recognized differences. That is, the groups with an initial value range of $Q[i, j](0) \in [0.5, 1]$ need one or two more role reassignment than the groups in $Q[i, j](0) \in [0, 1]$ to approach the 80/20 distribution, approximately $(10 - 9)/9 = 11\%$ slower on average. That is to say, if the groups have more qualified individual agents, the 80/20 distribution needs more reassignments.

TABLE III
COMPARISON BETWEEN TWO DIFFERENT δS

m	δ=1.05			δ=1.10		
	Max	**Ave**	**Min**	**Max**	**Ave**	**Min**
172	13	10	8	13	10	7
188	13	9	8	13	10	8
204	14	9	8	13	9	8
220	13	9	7	12	9	8
236	14	9	7	13	9	8
252	12	9	7	12	9	8
268	12	9	7	12	9	7
284	11	9	7	11	8	7
300	11	8	7	11	8	7
316	11	8	7	11	8	7

TABLE IV
COMPARISON BETWEEN DIFFERENT INITIAL Q VALUE RANGES

m	$Q[i, j]$∈[0,1]			$Q[i, j]$∈[0.5,1]		
	Max	**Ave**	**Min**	**Max**	**Ave**	**Min**
172	13	10	8	16	11	9
188	13	9	8	14	10	9
204	14	9	8	14	11	9
220	13	9	7	14	10	9
236	14	9	7	13	10	8
252	12	9	7	13	10	9
268	12	9	7	14	10	8
284	11	9	7	13	10	8
300	11	8	7	12	10	8
316	11	8	7	13	10	8

TABLE V
COMPARISON BETWEEN DIFFERENT INITIAL Q VALUE AND L^e VALUE DISTRIBUTIONS

m	**Uniform Distribution**			**Normal Distribution**		
	Max	**Ave**	**Min**	**Max**	**Ave**	**Min**
172	13	10	8	15	7	5
188	13	9	8	18	7	4
204	14	9	8	16	6	5
220	13	9	7	11	6	5
236	14	9	7	12	6	5
252	12	9	7	10	6	4
268	12	9	7	10	6	4
284	11	9	7	10	6	5
300	11	8	7	9	5	5
316	11	8	7	9	6	5

F. Simulation 6

In the simulation, $Q[i, j](0) \in [0, 1]$ $(i \in A,\ j \in R)$ (Gaussian distribution with the mean $= 0.5$ and the standard deviation $= 0.21$) and $L^e[i] \in [-0.5, 0.5]$ $(i \in A)$ (Gaussian distribution with the mean $= 0$ and the standard deviation $= 0.5$). We use the same settings as those in Simulation 3. Table V presents the results for $\delta = 1.05$.

Compared with the uniform distributions, normal distribution groups approach the 80/20 distribution faster than the uniform distribution groups, about $(9 - 6)/9 = 33\%$ faster on average. Also, in a normal distribution, the ρs are more dynamic than those in uniform distributions, i.e., some groups need more reassignments and some less.

G. Simulation 7

In Simulation 4, we notice that there is not much difference when we have different δ values. In this simulation, we try to

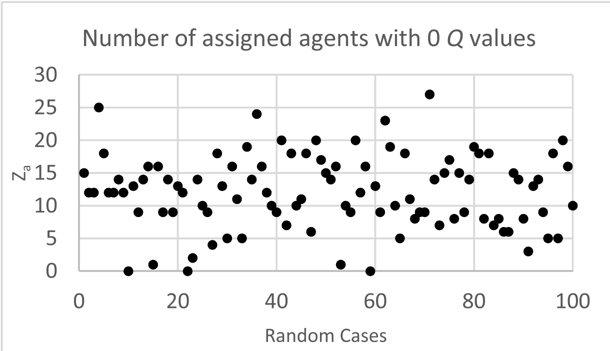

Fig. 7. Number of assigned zero Q value agents.

set Q values in a different way from (4)

$$Q[i,j](t+1) = Q[i,j](t) \times (1 + L^e[i]) \times \delta, \quad (i \in A, j \in R) \tag{5}$$

where $t = 0, 1, \ldots, k$ to mean the tth reassignment and $Q(0)$ means the initial Q. By (5), we mean that the $Q(t+1)$ values are all changed from $Q(t)$ by δ whatever the agents are assigned to roles or not. This idea follows the fact that a person's qualification value for a role increases with not only role-playing experience but also personal development.

In this simulation, other settings are the same as those in Simulation 4. Interestingly, we obtain the same conclusion as that of Simulation 4, i.e., the factor δ does not affect evidently the ρs. Table VI shows two sets of the collected data.

TABLE VI
COMPARISON BETWEEN TWO DIFFERENT δS [Q IS REVISED BY (9)]

m	δ=1.05			δ=1.10		
	Max	Ave	Min	Max	Ave	Min
172	13	9	7	13	9	8
188	13	9	7	13	9	7
204	12	9	7	12	9	8
220	12	9	7	13	9	7
236	12	9	7	12	9	7
252	12	9	8	12	9	7
268	11	8	6	11	8	7
284	11	8	7	11	8	7
300	11	8	7	11	8	7
316	12	8	6	10	8	7

H. Simulation 8

All the simulations just stop when the distribution approaches 80/20. What happens if the reassignments continue? We assure that such a simulation may create 90/10, 95/5, and even worse distributions. However, the reassignments are meaningless after the 80/20 distribution happens. Let us explain the reason. From the presented random case in Fig. 7, we notice that three agents holding zero ($<$0.005) Q values are assigned with roles. This is an indication of the reason why it is not rational to continue reassignments without serious reformation of the society. That is, there will be more and more zero Q value holders in the assignments. Zero Q value holders can be translated as death, inability, or other unsustainable states. According to the definition of GRA, an assignment with zero Q value holders means that the group (the community or the society) is not workable.

According to the assumption of RBC and GRA, there is a manager or BOG for a society. Usually, the manager should not allow the society to continue such role assignments. This should be a reason for 80/20 distributions not to worsen, e.g., 85/15, 90/10, or more.

With this clue, we design a new simulation. Setting 100 initial Qs, where $Q[i,j](0) \in [0,1]$ $(i \in A,\ j \in R)$ and follows the uniform distribution. We use $m = 172$ to mean that 10% of the people do not have jobs, $n = 4$, $L = \{1, 5, 25, 125\}$, $\sum_{j=0}^{3} L[j] = 156$, $L^e[i] \in [-0.6, 0.6] (i \in A)$, and $\delta = 1.05$. We use (4) to revise Qs after reassignment. Fig. 7 presents the 100 random cases and the number of assigned agents with zero Q values, denoted as Z_a, when the 80/20 distribution is approached. Zero Q values mean those less than 0.005 as we use two decimal points as the precision.

Other experiments use L^e from $[-0.5, 0.5]$, $[-0.4, 0.4]$, $[-0.3, 0.3]$, and $[-0.2, 0.2]$ and the data are shown in Table VII.

Table VII confirms that when a society approaches the 80/20 distribution, it starts to let unqualified agents work for the social roles and is not acceptable [7]. In Table VII, % means the percentage of the random cases having $Z_a > 0$. For example, when individual differences are large, i.e., $[-0.6, 0.6]$, 97% of cases have roles played by unqualified agents. Fortunately, when individual differences are small, i.e., $[-0.2, 0.2]$, the group is still workable. However, the qualification values for roles are very small, i.e., 10% of agents have a qualification value less than 0.01 (the two bottom lines of Table VII). To generalize what is presented in Table VII, we can state that the society is becoming unstable when 80/20 happens and keeping optimizing role assignment makes the society unhealthy. In other words, a worse distribution, e.g., 85/15, makes the society unstable or unsustainable.

Some new research results mentioning worse distributions of 90/10, 50/5, 30/2, or even 25/1 [3]. These situations require the manager or BOG of a society to take special actions to keep the society sustainable including welfare, training, or other policies to avoid roles being played by the zero Q value holders.

I. Simulation 9

We set up a new experiment with the same settings as Simulation 4 but introduce a weight vector $W = [8\ 4\ 2\ 1]$ to mean the different importance of the corresponding roles. Now we use $Q'[i,j] = Q[i,j] \times W[j]$ to replace $Q[i,j]$ in Definition 1 $(0 \le i < m, 0 \le j < 4)$. The results shown in Table VIII confirm our prediction. That is, we have smaller ρs in this simulation, compared with the numbers in Simulation 4 and the right half of Table III.

The simulations can continue to introduce more factors or schemes of change. The more factors are considered, the more details of social phenomena can be revealed and explained. We can continue in this direction in the future.

V. DISCUSSION

From Section IV, the 80/20 phenomenon is formed by individuals and team inceptions. The σ^*_{20}/σ^* can reflect many

TABLE VII

Z_as (<0.005) IN DIFFERENT RANGES OF L^e VALUES

$L^e \in$	Max	Ave	Min	%	σ(Ave)	ρ(Ave)
[-0.6, 0.6]	23	11	0	97	1817	8
[-0.5, 0.5]	18	6	0	89	1697	10
[-0.4, 0.4]	16	2	0	54	1952	12
[-0.3, 0.3]	7	0	0	11	2165	15
[-0.2, 0.2]	0	0	0	0	2589	21
Set Q value as 0 if it is less than 0.01.						
[-0.2, 0.2]	4	0	0	8	2596	21

meanings in a society, such as the rate of the contributions, shares, or wealth distributed to the 20% people of the whole society, i.e., the 80/20 distribution is not formed by one-time role-assignment but by a series of role reassignments.

A. Society's Perspective

It is evident that the L^e values present the most impact on the ρs. The difference between the most energetic agents and the least energetic agents determines the pace of the 80/20 distribution's formation. The ρs indicate the speed for a society to approach the 80/20 distribution. In fact, other than energy, the L^e values can be explained as the levels of strength, knowledge, intelligence, wisdom, goals, intentions, or other personal characteristics of an individual in a society. Therefore, from the result of the simulations, we can state that if there are differences among agents in personal characters, the 80/20 distribution is a must through a series of role reassignment, sooner or later. The more role reassignments per interval unit, the sooner the 80/20 distribution is approached.

The results also show that agents are competing with each other. With long-term social activities, a few competitive agents (20%) will occupy most part of the social shares, including money, products, and wealth. Gradually, most less competitive agents (80%) can only share the leftover part (20%).

From the simulations, we also notice that more idle agents do not make many differences for a group to approach the 80/20 distribution. The reason is that those idle agents do not contribute anything to the team performance and do not take shares from the society. The impact of these idle agents is that we need more agents to compose the top 20% agents.

A very typical data (Simulation 4) inform us an interesting fact that when the L^e values belong to $[-0.5, 0.5]$. Note that, $[-0.5, 0.5]$ expresses the energy difference of 1. It means that one agent can have three times of individual energy value of the others, i.e., 1.5:0.5. The number of reassignments to approach the 80/20 distribution is from 7 to 14. If we extend the group to express a country, where each agent means a hundred thousand people and each reassignment means a social reconfiguration and happens in 3–5 years. At the latest, around 70 (=5 × 14) years after the country is established with even distributions, the 80/20 distributions must occur. The earliest time for a country to obtain the 80/20 distribution is 21 (=3 × 7) years.

We conclude that the following factors have little impact on the formation of the 80/20 distribution from the society's perspective: 1) the social incentive factor δ (Simulation 4); 2) initial random Q matrix (with even or Gaussian distribution) (Simulations 5 and 6); and 3) the distributions of random Q values and L^e values (Simulation 6).

TABLE VIII

ρs AFTER W INTRODUCED

m	$Q[i, j]$ ∈[0,1] (Uniform Distribution) , δ=1.1		
	Max	**Ave**	**Min**
172	9	6	5
188	9	6	5
204	9	6	5
220	8	5	5
236	9	5	4
252	8	5	4
268	8	5	4
284	7	5	4
300	7	5	4
316	6	4	4

TABLE IX

INITIAL Q VALUES AND L^e VALUES OF THE AGENTS THAT ARE INITIALLY IN $A^{20\%}(T^*)$ AND FINALLY KICKED OUT

Role Index / Agent Index	0	1	2	3	L^e
19	0.1	0.53	0.09	**0.41**	-0.52
57	0.95	0	0.35	**0.67**	-0.52
65	0.04	0.17	0.16	**0.15**	0.44
81	0.17	0.04	0.24	**0.21**	0.43
125	0.58	0.65	0.33	**0.17**	0.43

If σ is taken as the collected social wealth and ρ as the indicator of time, then a larger individual difference leads to a faster collection of social wealth (Simulation 8, Table VII; Simulation 9, Table VIII). To make 80/20 distribution happen later, we may need to shrink the impacts of individual differences. However, this shrinking is unfair for energetic people. This contradiction reflects another issue of equality or equity [17]. A social paradox is revealed, i.e., if we encourage individual difference, we collect social wealth more quickly but the gap between haves and have-nots becomes larger; if we discourage individual difference, we have to accept a slower social development or collect social wealth more slowly.

B. Individual's Perspective

From the data collected through Simulation 7, we extract a random case to analyze individuals' contributions or distributions. The setting of this random case is $m = 172$, $n = 4$, $L = \{1, 5, 25, 125\}$, $L^e[i] \in [-0.6, 0.6] (i \in A)$, and $\delta = 1.05$. The $Q(0)$ matrix ($Q[i, j](0) \in [0, 1]$, $i \in A$, $j \in R$) is too large to present.

We present some Q values to help the analysis. In this case, the group uses one initial assignment (0) plus eight reassignments (1–8) to obtain the 80/20 distribution. A typical phenomenon is that most (85.29%) agents (29 out of 34 agents) with top energy values will finally be the top 20% agents (34).

For the five agents that are kicked out of the top 20% finally, the related $Q(0)$ and L^e values are shown in Table IX. For the five agents that join the top 20% at the assignment making the 80/20 distribution, the related $Q(0)$ values are shown in Table X.

In Tables IX and X, the bolded numbers mean that the agents are assigned to the corresponding roles. All the five agents that are kicked out are assigned to the roles that are not their most qualified ones, while those five agents finally joining

TABLE X

INITIAL Q VALUES AND L^e VALUES OF THE AGENTS IN $A^{20\%}(T^*)$

Agent Index \ Role Index	0	1	2	3	L^e
30	0.54	0.28	**0.86**	0.14	0.41
<u>52</u>	<u>0.42</u>	<u>0.68</u>	<u>0.16</u>	<u>0.06</u>	<u>0.41</u>
82	0.56	0.14	0.09	**0.98**	0.39
117	0.39	**0.86**	0.04	0.15	0.39
152	0.66	0.32	0.29	**0.68**	0.37

TABLE XI

Q VALUES OF AGENT 52 IN THE REASSIGNMENT

Assignment \ Role Index	0	1	2	3
0	0.42	0.68	0.16	0.06
1	0.59	0.96	0.22	0.09
2	0.83	**1.43**	0.31	0.13
3	1.16	**<u>2.11</u>**	0.44	0.18
4	1.64	**3.12**	0.62	0.25
5	2.31	**4.62**	0.87	0.36
6	3.26	**6.84**	1.23	0.5
7	4.6	**10.13**	1.74	0.71
8	6.48	**<u>14.99</u>**	2.45	1

TABLE XII

INITIAL Q VALUES AND L^e VALUES OF THE AGENTS THAT LOSE ROLES

Agent Index \ Role Index	0	1	2	3	L^e
1	0.67	0.51	0.03	0.43	-0.52
7	0.28	0.11	0.03	0.04	-0.59
12	0.6	0.17	0.76	0.02	-0.55
16	0.63	0.09	0.7	0.23	-0.47
19	0.1	0.53	0.09	0.41	-0.52
31	0.03	0.52	0.31	0.06	-0.37
45	0.01	0.73	0.26	0.95	-0.56
55	0.17	0.09	0.85	0.26	-0.56
106	0.33	0.45	0.55	0.2	-0.59
135	0.72	0.46	0.27	0.04	-0.43
137	0.93	0.83	0.23	0.68	-0.57
138	0.21	0.38	0.29	0.18	-0.57
140	0.78	0.03	0.27	0.92	-0.57
142	0.66	0.45	0.53	0.1	-0.56
158	0.69	0.77	0.65	0.05	-0.38
166	0.57	0.63	0.6	0.65	-0.58

the top 20% agents are assigned to their most qualified roles. The agents kicked out of the top 20% either have negative energy values or small initial qualification values.

There is an exception that agent 52 does not have a high initial Q value and is not assigned any role in the first two (0, 1) assignments. However, it starts to get a position from the third (#2) assignment. Another interesting fact is that agent 52 does not always belong to the top 20% agents. It enters the top 20% only in the fourth (#3) and ninth (#8) assignments. Agent 52 reflects a person who is at the edge, if we scatter the top 20% agents in a circle, where the agents in the center have more shares than those far from the center.

Table XI shows the evolution of agent 52 in the assignment, where the bolded numbers mean that it is assigned with a role.

When approaching the 20/80 distribution, all the agents (16) that are not assigned with roles have their Q values down to 0 or near 0s. The initial Q values of these 16 agents and their energy values are shown in Table XII.

The limitations of the presented simulations come from the assumptions. We assumed that the number of agents in a society is constant. Also, we use the one-time assignment to express the distribution and wealth accumulation. These assumptions have rationalities to some extent. However, there might be more pertinent assumptions for future work.

VI. RELATED WORK

There are many applications of the Pareto 80/20 principle in various areas [1, 18–23]. Chen *et al.* [18] use the 80/20 rule notations in the area of library management as well as an index approach to the modeling. Their results show that the time factor has no effect on the shape of the Pareto curve $\theta(x)$, where x is the fraction of total holdings with more than a number of circulations and θ is the fraction of total circulations due to the holding x. The curve is determined by an entry rate and the quantity of holding. Singson and Hangsing [19] investigate the implication of the 80/20 rule in the large academic library consortia in India. They criticize the 80/20 rule for "sometimes indicating a pattern that is widely off the mark" but find it effective for academic administrators to justify purchase through usage statistics for cost-effectiveness journals and improve the quality in journal acquisition.

Pocatilu *et al.* [20] apply the 80/20 principle in quality control during software development, i.e., 80% of users are actually using only 20% of the features and 80% of errors are generated by 20% of the detected bugs. Yamashita *et al.* [4] examine the applicability of the Pareto principle to core development teams in open-source software development. Their findings indicate that the 80/20 rule is not compatible with the core teams of many GitHub projects. We believe that it is because the core teams for GitHub projects are all among the initial steps of development. Grosfeld-Nir *et al.* [22] propose an analytical tool (an index including A, B, and C category) to assist managers in applying the 80/20 principle to accomplish their tasks. They combine their proposed index with the Pareto focusing methodology including steps of classification, differentiation, and allocation. Cooper *et al.* [1] study infectious disease control where the Pareto rule states that 80% of transmission is done by 20% of the individuals, called super-spreaders. They conclude that the 20% "super-spreader" cohort accounts for only part of the infections. O'Neill [23] study the errors in student writing, aiming to identify what is known as "the critical few" errors that could improve writing up to 80%. They conclude that the Pareto charts demonstrate a consistent focus on 3–6 errors (e.g., comma, words, passive, and spelling) thus proving the point for school instructors to focus on the "vital few" to improve writing quality by a large amount (≈80%).

Matthews [24] argues that equality of opportunity (EOO) would make every parenting choice a matter of public policy, to be regulated accordingly. She states that EOO is a distraction, which takes people's eyes off the prize and spreads the logic making actual inequality worse. Bommier and Zuber [25] try to reveal the nature of the Pareto principle. They show that the Pareto principle is generally not true in time-consistent intertemporal models where some uncertainty prevails. In conclusion, they cannot find two social Paretian social observers, with one being more inequality than the other one. That is, there must be some uncertainty. Kaplow and Shavell [26] think that social policies should be assessed "entirely on the basis of their effects on individuals' well-being." They demonstrate how notions of fairness perversely reduce welfare and prove an account of notions of fairness that explains their intuitive appeal in their conclusion that is, social policies should not be treated as independent principles in policy assessments. Rosanvallon [27] believes that EOO is not just a measurement of distribution but a social relation. Theories of EOO should be a foundation for policy making to reduce inequalities. Benhabib *et al.* [28] explore the dynamic and stationary wealth distribution of wealth using Pareto distribution. They conclude that capital income and estate taxes can significantly reduce wealth inequalities and increase the institutions favoring social mobility. Levy and Levy [29] study the implication of high wealth levels of Pareto wealth distribution and whether this difference is due to differential talent or simply luck. They believe that the empirical observation of the Pareto distribution implies that luck but not differential talent is the main driving force toward inequality at high wealth levels. Even though they try to reveal the nature of the Preto 80/20 distribution, their methods, goals, and conclusions are very different from this article.

We simulate phenomena in social systems in [8] and [31]. The results confirmed several common-sense statements. Matrix Q brings in various social meanings, which provide numerous opportunities for social simulations using E-CARGO and GRA. Our previous work on RBC [5], [6], E-CARGO [5]–[12], and GRA [7]–[12] provide a solid foundation for the proposed research. Self-citations seem unavoidable.

VII. Conclusion

The contribution of this article is a novel way to study the Pareto 80/20 principle from the viewpoint of iterative role assignment, i.e., using the GRA to simulate the trend of distributions.

Other interesting findings are as follows.

1) The 80/20 principle is untrue when a society is formed at the beginning (Theorem 1).
2) The 80/20 phenomenon is produced by multiple optimized reassignments of roles to the people (agents) in the society. If agents are different, the 80/20 distribution is a must.
3) The formation of the 80/20 distribution can be slow or fast due to different individual or social incentives. The most influential factor in the speed of 80/20 distribution formation is individual differences.
4) The 80/20 principle exists because worse distributions make a society unstable and unsustainable. The administrator usually takes actions to avoid the original trend continuing when the 80/20 distribution happens, or the society does not exist anymore.
5) This article reveals a social paradox: emphasizing individual differences inevitably leads to rapid social wealth accumulation and polarization and ignoring such disparities certainly causes slow social wealth accumulation.

We may conduct interesting investigations in the future.

1) Based on the proposed method, it is very interesting if we assume that a society grows in populations. This assumption is more pertinent for countries in the world because most countries' populations are increasing if there are no wars or disasters.
2) A more challenging and interesting research is to conduct simulations for open or hierarchical societies, i.e., the agents can leave one society and join other societies, agents may be promoted to an upper-level society from a lower one.
3) We may consider explicit wealth collection in the consecutive assignments and may simulate more details of social development. Note that, (4) and (5) reflect implicitly the wealth collection in an abstract way.
4) Following the clue of this article, we may apply GRA, RBC, or E-CARGO to other economic or social laws and rules to assure, confirm, or reveal hidden knowledge for these laws, such as the Peter principle [32] and Matthew effect [33].
5) Agent modeling [34]–[38] is widely used in simulations. It is an interesting topic to analyze and compare the simulation results of GRA-based and agent-based approaches.

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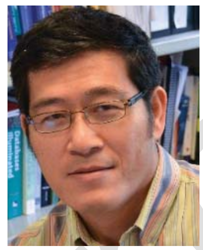

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