Endogenous Power Assignment and Power Disparity

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Abstract

The importance of power in social and organizational relationships has long been recognized. Yet, the research on power does not provide a univocal definition or presents consistent findings with regard to the level of power disparity and merit based assignment of power. Using Newtonian laws, this paper conceptualizes power simultaneously as a relational capacity, behaviors attached to this capacity, and realization of power in the form of influence. We extend the formal design perspective, and allow for informal power structures and evolutionary dynamics. we employ the agent-based simulation method of an evolutionary computation technique called particle swarm optimizer algorithm (PSO). PSO offers a formal representation of the group dynamics which maps directly to our conceptualization of power, and the interaction between individuals due to power differences is embedded into the search process. The results suggest that organizational design of power structures should consider both the level of power disparity and evolutionary dynamics of power assignment. Finally, this study highlights environmental complexity and magnitude of high power as moderators in comparing different power models.

Key words: Power, organizational design, agent based simulations, particle swarm optimization

Introduction

Organizations are constantly in search of the best strategic alternatives within their respective environments [8, 17]. Apart from (boundedly-) rational strategic choices, an organization's strategic direction is determined by relative differences in power [8]. Indeed, power has long been recognized as an essential element in social and organizational relationships [1]. Hence, determining the most suitable configuration of power differences within a group is an important organizational design question.

Despite its popularity, or perhaps because of it, there is a plethora of theoretical conceptualizations of power (see [3, 4] for a review). Yet, it is a long standing discussion in power literature whether power is an individual capacity stemming from various power bases (e.g. network centrality, hierarchical rank, holding scarce resources, etc.), or whether it is an individual ability to achieve desired outcomes despite the resistance [4]. Rather than favoring one side over the other, this paper shows that it is possible to provide a formulation that integrates those separate but intertwined dimensions of power simultaneously. Using the allegory between Newtonian mechanics and power, we conceptualize power as (1) a relational individual capacity that (2) attributes certain behaviors to the individuals harnessing this capacity, and (3) is exercised in the form of influence on others [10, 14]. To be able to capture these three dimensions of power simultaneously, we model the power in terms of Newtonian Laws. In this model, an individual's power as her/his capacity is represented by the mass of the individual, and the behavior as result of this capacity is expressed as the attraction and resistance in terms of Newtonian forces. Then, the realization of power can be expressed as the change in an individual's position.

Furthermore, empirical findings with respect to level of power disparity and merit based appointment of power remain contradictory [1]. We attribute this lack of consensus on power to the fact that power is a complex phenomenon. For such complex phenomena, agent-based simulation methods are frequently applied as powerful theory building tools in the organization and strategy literature [6]. However, existing simulation studies in power research are mostly limited to 'formal design perspective' (see e.g. [17, 21]). Studies from the formal design perspective agree to define the power and power disparity in terms of the formal authority, that is, the hierarchical position, and to assign power exogenously. However, [21] write that power is not confined to the formal structure of hierarchies. [12] suggests that informal structures in the organization may be more critical than the formal structure. In addition, power is not a stationary phenomenon but rather evolutionary. That is, individuals may evolve, and their power may change in time. In this paper, we employ the agent-based simulation method of an evolutionary computation technique called particle swarm optimizer algorithm (PSO). PSO enables us (1) to model cooperative action of a group of individuals trying to find the best solution, (2) to model heterogeneous individuals with varying power levels, and (3) to capture multi-dimensional nature of power's conceptualization.

Research gaps in terms of the lack of a univocal conceptualization of power, discrepant findings, and limited focus of formal design perspective constitute the main targets of this study. Our first contribution is articulation of a multidimensional conceptualization of power. Second, we contribute to the organization design research by drawing new perspectives to the design question of finding a superior configuration of power differences not only in terms of level of power disparity but also how power is assigned. We compare six power models which are categorized according to their level of disparity and power assignment method. Our results suggest that the choice between groups with low, high, and moderate power disparity depends on whether power assignment is based on competency or not. Our third contribution is that we go beyond the formal design perspective and allow informal structures as well as evolutionary dynamics in power formation. In doing so, we add another contribution to the strategy and organization literature by introducing an agent-based simulation technique that can model group search for the best solutions in the light of rational choices and power differences where there is still room for mere chance.

Modeling Power

To model power, we adopt an agent-based perspective such that each individual (agent) lives in and moves through a multi-dimensional space. A utility value (for example fitness, profit or performance) is assigned to an individual's position in the space. Individuals operate cooperatively in groups that represent an organizational unit or a company. The objective of the group is to find the position (solution) that yields the highest utility value. To illustrate, consider a Top Management Team (TMT) of an organization. As a group, the TMT tries to maximize profit of the organization which requires finding the optimal solution to a continuous multidimensional problem such as determining amount of R&D spending, degree of penetration to new markets, allocation of budget to marketing activities, etc. Each TMT member has his/her own understanding of the best solution. In their search of finding the best solution, they are affected by their own previous findings and those found by their group members. Additionally, they influence others in the group by means of their power. We begin constructing this model with conceptualization power in the next subsection. Later, the search dynamics of the model will be introduced.

Conceptualization of Power

The research on power has become fragmented [10], as the conceptualizations of power are quite varied: from institutional, resource-based, and outcome-based perspectives of power to interpretive, neo-structural, radical (such as Lukesian, Gramschian or Habermasian), and Foucaultian views of power [3, 4]. This variation makes it difficult to provide a single comprehensive definition that incorporates different perspectives on power simultaneously [10]. Despite the variety of the conceptualizations of power, most of them include one or more of the following dimensions: power as a relational individual capacity, behaviors attributed to having low or high power, and realization of power as influence on others [10, 14]. We model power such that all these dimensions are captured.

Let an individual j be located at a point with its coordinates given by $D \times 1$ vector $\boldsymbol{x}_j$ where D is the dimensionality of the space. S/he has a mass m_j (power as capacity). The individual exerts a force in relation to her/his power on another individual at $\boldsymbol{x}_i$ whose mass is m_i (behaviors using the power capacity). This force acts along and $\boldsymbol{x}_i$ and $\boldsymbol{x}_j$ and causes a change in the position of i such that the individual at $\boldsymbol{x}_i$ is accelerated toward the individual at $\boldsymbol{x}_j$ (exercised power). That is, the power embedded in the size of the mass is exercised through the gravitational force and brings out desired change in the other individual's position. This force is proportional to the product of their mass and inverse proportional to the distance between individuals. This principle is known as Newton's Law of Universal Gravitation. Formally, size of the force, f_{ij}, acting on individual i by j is

$$f_{ij} = G\frac{m_i m_j}{\|\boldsymbol{x}_j - \boldsymbol{x}_i\|^2}, \tag{1}$$

where $\|\boldsymbol{x}_j - \boldsymbol{x}_i\|^2$ is the squared Euclidean distance between points $\boldsymbol{x}_i$ and $\boldsymbol{x}_j$, and G is the constant of proportionality that can be set without loss of generality to 1 in our context. The force, f_{ij}, on individual i due to j points from $\boldsymbol{x}_i$ toward $\boldsymbol{x}_j$. The direction of the force is given by

$$\boldsymbol{u}_{ij} = \frac{\boldsymbol{x}_j - \boldsymbol{x}_i}{\|\boldsymbol{x}_j - \boldsymbol{x}_i\|}. \tag{2}$$

Then, the directed force vector, $\boldsymbol{f}_{ij}$, is obtained by multiplying (1) and (2), that is,

$$\boldsymbol{f}_{ij} = f_{ij}\boldsymbol{u}_{ij} = \frac{m_i m_j}{\|\boldsymbol{x}_j - \boldsymbol{x}_i\|^2}\frac{\boldsymbol{x}_j - \boldsymbol{x}_i}{\|\boldsymbol{x}_j - \boldsymbol{x}_i\|} = \frac{m_i m_j}{\|\boldsymbol{x}_j - \boldsymbol{x}_i\|^3}(\boldsymbol{x}_j - \boldsymbol{x}_i). \tag{3}$$

In a group of N individuals, an individual's movements is accelerated or decelerated toward the total force exerted on him/her by $N - 1$ individuals in the group. Within a system of N-individuals interacting only under mutual gravitation, the total force on an individual expressed as

$$\boldsymbol{f}_i = \sum_{\substack{j=1\\ j\neq i}}^{N} \boldsymbol{f}_{ij} = \sum_{\substack{j=1\\ j\neq i}}^{N} \frac{m_i m_j}{\|\boldsymbol{x}_j - \boldsymbol{x}_i\|^3}(\boldsymbol{x}_j - \boldsymbol{x}_i) . \tag{4}$$

Acceleration as a result of the total force exerted on an individual is derived by utilizing Newton's Second Law of Motion. It states that sum of the forces on an individual is equal to the product of his/her mass times his/her acceleration. For the individual i, using (3) and (4) yields

$$m_i\boldsymbol{a}_i = \sum_{\substack{j=1\\ j\neq i}}^{N} \frac{m_i m_j}{\|\boldsymbol{x}_j - \boldsymbol{x}_i\|^3}(\boldsymbol{x}_j - \boldsymbol{x}_i) = m_i\sum_{\substack{j=1\\ j\neq i}}^{N} \frac{m_j}{\|\boldsymbol{x}_j - \boldsymbol{x}_i\|^3}(\boldsymbol{x}_j - \boldsymbol{x}_i) \tag{5}$$

with $1 \le i \le N$. Dividing both sides by m_i gives the acceleration

$$\boldsymbol{a}_i = \sum_{\substack{j=1\\ j\neq i}}^{N} \frac{m_j}{\|\boldsymbol{x}_j - \boldsymbol{x}_i\|^3}(\boldsymbol{x}_j - \boldsymbol{x}_i) . \tag{6}$$

According to (6), an individual is attracted more toward powerful individuals who are cognitively closer compared to the distant individuals with low power. This formulation is in line with Latane's first principle of social impact stating that the amount of impact experienced by an individual due to others is proportional to power of a given influence source, its closeness, and number of sources [15: 344].

Models of power differences

This study investigates the performance of different power distribution scenarios within a group categorized according to the level of disparity and how power is appointed. *Power disparity* within a group is defined as the differences in concentration of power among group members [11].

Evolutionary dynamics of power in this paper considers how the power is assigned to individuals. If power is assigned to an individual ex-ante and it is stationary over time, we call it as exogenous power assignment. On the other hand, power assignment is called as endogenous if the initial power changes from one time period to another based on an individual's relative past performance. The six power disparity models we focus on are summarized in Table 1.

The *evolutionary* model defines the power of individuals endogenously and dynamically according to their performance in the previous period according to the following formulation: At time $t \in \{1, \dots, \mathrm{T}\}$, let $\psi(\boldsymbol{x}_i^t)$ be the performance (fitness) of individual i located at $\boldsymbol{x}_i^t$, $\max_j \psi(\boldsymbol{x}_i^t)$ be the best performance and $\min_j \psi(\boldsymbol{x}_i^t)$ be the worst performance of the group. Furthermore, let m^{high} and m^{low} indicate predetermined mass sizes of the individual with highest and lowest power respectively. Then, the endogenous assignment of power can be formulated as

$$m_i^{t+1} = \frac{\psi(x_i^t) - \min_j \psi(x_j^t)}{\max_j \psi(x_j^t) - \min_j \psi(x_j^t)} (m^{high} - m^{low}) + m^{low}, \quad \forall i, j \in \{1, \dots, N\}. \tag{7}$$

According to (7), an individual obtains the highest power if s/he finds the best solution in the previous period, and zero power in case that s/he is the poorest performer in the previous period. Since having zero power is not meaningful and realistic in the context of organizations, the minimum level of power is set as $m^{low} > 0$.

Power Model	Disparity	Description
Exogenous power models		The power structure does not change over time.
Autocratic	High	There is only one powerful individual in the group who is exogenously assigned ex-ante. The rest of the group has low power.
Bureaucratic	Moderate	Ex ante individuals ranked linearly between high and low power.
Egalitarian	Low	Every individual has low power.
Endogenous power models		Power is appointed based on the performance in the previous iteration
Meritocratic	High	The individual who achieves the best performance in the previous period receives high power in the following period; the other group members have low power.
Diarchy	[Moderate, High]	In addition to an exogenously assigned powerful individual, in each period the best performing individual in the previous period has high power. The rest of the group has low power. The level of disparity for diarchy is less than autocratic and meritocratic models, but higher than the evolutionary and bureaucratic models.
Evolutionary	Moderate	Individuals are ranked according to their performance in previous period. That is, individual with the best solution becomes the most powerful in the next period, whereas the worst performer gets low power, and rest of the group is ranked in between.

Table 1: Models of Power Differences Based on the Level of Disparity and Endogeneity

Simulation Model

Particle swarm optimization

In this paper, we employ the agent-based simulation method of an evolutionary computation technique called particle swarm optimizer (PSO). PSO has showed to be very efficient in various fields in science and engineering [2]. To our knowledge, this paper is one of the first studies that apply PSO in strategy and organization literature (see [18] for taxonomy of studies using PSO).

In the standard PSO, besides the initial velocity and position, an individual determines its movement according to (a) the best solution found due to his/her local search, and (b) the best solution by the group. We add a third element to the standard PSO that is the total force exerted on an individual.

Let us briefly formalize the PSO. The reader is referred to [5] for further details. At time period (iteration) $t \in \{1, \dots, T\}$, the location of individual *i* on the search space is presented by the *D*-dimensional position vector $\boldsymbol{x}_i^t = (x_i^t, x_{i2}^t, \dots, x_{iD}^t)$. The performance (fitness) of an individual at $\boldsymbol{x}_i^t$ is denoted as $\psi(\boldsymbol{x}_i^t)$. The best performance reached by individual *i* so far due to her/his local search is defined as $pbest_i^t$ and the location of $pbest_i^t$ is $\boldsymbol{p}_i^t$. The value of the best performance found by the group is denoted as $gbest^t$ at position $\boldsymbol{g}^t$. When the objective is to maximize $\psi(\boldsymbol{x})$ over $\boldsymbol{x}$, $pbest_i^t$ and $gbest^t$ are monotone increasing since they are updated only if a better solution is found. Individual *i* changes his position according to the velocity vector $\boldsymbol{v}_i^t = (v_i^t, v_{i2}^t, \dots, v_{iD}^t)$. In the PSO, the velocity and location of each individual is updated on the time period *t*+1 according to

$$\boldsymbol{v}_i^{t+1} = \phi \boldsymbol{v}_i^t + c_1\varphi_1(\boldsymbol{p}_i^t - \boldsymbol{x}_i^t) + c_2\varphi_2(\boldsymbol{g}^t - \boldsymbol{x}_i^t) + c_3\varphi_3 \sum_{\substack{j=1 \\ j\neq i}}^{N} \frac{m_j}{\|\boldsymbol{x}_j - \boldsymbol{x}_i\|^3}(\boldsymbol{x}_j - \boldsymbol{x}_i) \quad (8)$$

$$\boldsymbol{x}_i^{t+1} = \boldsymbol{x}_i^t + \boldsymbol{v}_i^{t+1} \quad (9)$$

where ϕ is the inertia weight. Second term in the right hand side indicates the acceleration due to the local search by particle *i* and the third term is the acceleration due to the global search. The fourth term is the insertion of (3) which states the acceleration due to gravitational forces within the group. $c_1, c_2, and\ c_3$ are the acceleration constants, $\varphi_1, \varphi_2, and\ \varphi_3$ are independent uniformly distributed between 0 and 1.

Note that (5) is in line with the paradigms proposed by [8] as the movement of the individual is influenced by the best solution that the individual has found so far as a result of his/her own search and the best solution that has been discovered by any member of the group (that is, the bounded rationality paradigm), and gravitational force exerted by others proportional to the mass and disproportional to the distance (that is, the politics and power paradigm) where there is still room for pseudo-randomness in the search (that is, the garbage can paradigm).

Fitness Function and the Landscape Roughness

To answer our research questions, it is necessary to analyze the collective performance of individuals in maximizing a fitness function $\psi(\boldsymbol{x})$ representing, for example, performance, profit, or innovations. We need to 'produce an arbitrarily large number of statistically identical problems for the simulated agents to solve' [16: 673]. We do so by using the Gaussian landscape generator [9].

The landscape generator consists of preselected number of multivariate normal distributions (i.e. Gaussian functions) with uniformly distributed means over a fixed *D*-dimensional space and varying covariance matrices. The height of each Gaussian is also random except the best one, whose value is set to ψ^* and the ratio *r* between the best and the second best is $r\psi^*$. Then, this landscape generator is simply defined as the maximum value over all Gaussians. The main parameter of interest is the complexity level of each landscape γ defined as the number of Gaussians. Note that when $\gamma = 1$, a rather simple unimodal landscape (only one global optimum with no local optima) is created. The number of peaks, that is, the number of local optima, increases with γ such that the actual number of local optima will be less or equal to γ due to the possibly overlapping Gaussian components. Figure 1a illustrates a landscape created with $\gamma = 1$ and Figure 1b with $\gamma = 30$ Gaussians in a two dimensional space within the range of [-2, 2]. Clearly, finding the optimum in Figure 1a is much easier than doing so in a complex landscape such as Figure 1b where there are many local optima and deep valleys.

a. b.

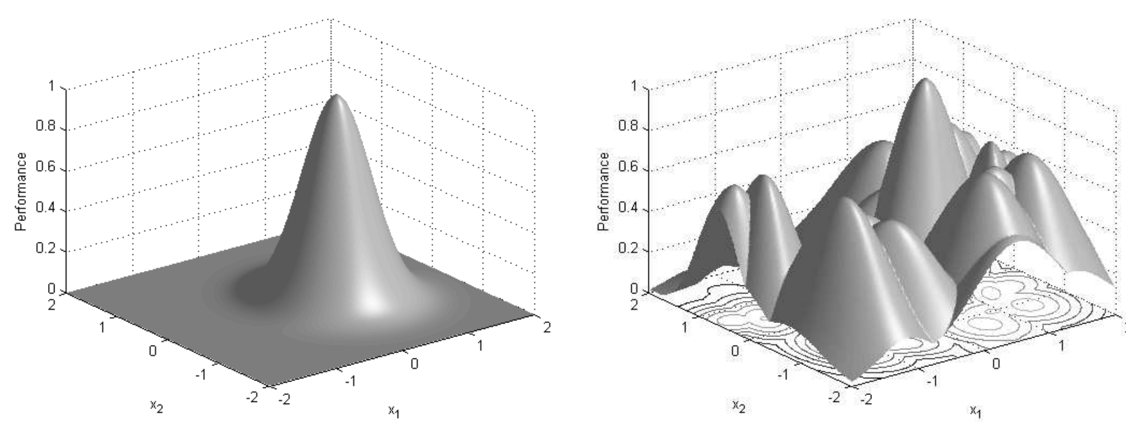

Figure 1: Example Landscapes Created Using the Gaussian Landscape Generator

Results

Experimental setting

The six power models were compared in terms of their performance and convergence for varying complexity levels. The performance of a power model is defined as the best function value $gbest^T$ reached by the group at the final iteration T of a simulation run. Similarly, the convergence t^*, is defined as the iteration number when the group converged to this performance level, $gbest^T$. To be able to see whole trajectory of the individuals for each of the power models, we allowed the algorithm to continue after achieving convergence at t^*, and only to stop when the maximum number iterations T is reached.

We first created the swarm. Swarm size is commonly considered to be between 20 and 50 in standard applications of PSO. However, in real world problem solving groups and organizational teams it is rare to have such big group sizes. For example, in their study of top managements in 67 U.S. based firms [20] report a mean group size of 10. Therefore, we considered a swarm of 10 particles in a D = 5 dimensional space. Then, for each complexity level, we created 2000 landscapes by using the Gaussian landscape generator. Individuals were randomly positioned on the landscape and random initial velocities drawn from the uniform distribution were assigned. Each power model was run on the same landscape, with the same initial positions and velocities. Hence, any observed difference in the convergence can be attributed to the power models only.

Parameter	***Value***	***Parameter***	***Value***
Swarm		*PSO*	
Number of particles (N)	10	Number of iterations (T)	1000
Maximum power (m^{high})	2	Maximum velocity (v^{max})	2
Minimum power (m^{low})	.1	Acceleration coefficients (c_1, c_2, c_3)	1.494
Problem space		Initial inertia weight (ϕ^1)	.9
Dimensionality (D)	5	Final inertia weight (ϕ^{1000})	.4
Range of search space	[-2,2]	Iteration for final inertia weight	1000
Range of number of components (γ)	[1, 30]	Bounce method	Wraparound
Value of the global optimum (ψ^*)	1		
Value of the highest local optimum (r)	.75		

Table 2: Parameters Used throughout Simulation Experiments

In Table 2 the full list of parameters is presented. PSO coefficients are parameterized according to default PSO settings: type 1`` model of [5] where the acceleration coefficients for local, c_1, and global search, c_2, were taken equal. The authors report these settings produced the best results in their experiments. Similarly, we set the acceleration coefficient for the gravitational attraction, c_3, to be equal to the other two acceleration coefficients. The equal acceleration coefficients enable a balance between exploitation due to individual search, exploration due to group search, and movement due to gravitational forces.

Power disparity under endogenous and exogenous power assignment

For the two outcome variables of performance and convergence, we performed MANCOVA by using power models as factors and complexity levels as covariates. Wilk's Lambda was significant for the main effects and the interaction effect ($p < .001$). Results showed significant main effects of power model and complexity on performance ($F(5, 359998) = 184.27$, $p < .001$; $F(1, 359998) = 36.16$, $p < .001$) and convergence ($F(5, 359998) = 86.71$, $p < .001$; $F(1, 359998) = 1110.63$, $p < .001$). We also found a significant interaction effect of the power model and complexity on performance ($F(5, 359998) = 51.73$, $p < .001$), and on convergence ($F(5, 359998) = 4.27$, $p = .001$.).

One of the drawbacks of statistical approaches in randomly generated large data sets is that even the smallest effects can turn out to be significant as the random error becomes very small due to the large number of points sampled [19]. Hence, to complement the statistical analyses, the results were visually presented in terms of performance profiles [7] in Figure 2. We define the proportion of a power model for the performance ratio within 5% range of the best performing model.

When the power is assigned exogenously, the results point out a main effect of power models and interaction effect between power models and complexity in terms of performance. The autocratic and egalitarian models outperform the bureaucratic model. The egalitarian model having a low level of disparity performs better than the autocratic model only for low complexity levels; however, this difference disappears as the landscapes become more complex. The results suggest that the relationship between group performance and level of disparity is not linear in terms of level of disparity. The relationship between complexity level and convergence of exogenous power models do not reveal any clear differences between power models.

Furthermore, in case of endogenous power assignment, a large main effect of power models and a slight interaction effect between power models and complexity for performance, and main effect for convergence can be observed. For all complexity levels, diarchy and meritocratic models which has high degree of power disparity provides the better performance than the evolutionary model. However, evolutionary model outperforms other two models in terms of convergence. Meritocratic model which has higher degree of disparity than the diarchy leads to higher performance. The relationship is reversed with respect to the convergence.

Lastly, when all power models are compared at the same time, in case of low environmental complexity, meritocratic model having endogenous power assignment and high power disparity represent equal performance as the egalitarian model where the power disparity is the lowest. However, meritocratic model outperforms all the others as the environment becomes more complex. Furthermore, the difference between diarchy, autocracy, and egalitarian models disappears with the level of complexity. In all cases, models with moderate disparity level (e.g. bureaucratic and evolutionary) lead to the worst performance relative to other models. Lastly, the results do not represent a clear distinction between models in terms of convergence.

Magnitude of high power

In this subsection we compare the power models by varying magnitudes of the high power, m^{high}. We ran 6 (power models) × 3 (low, moderate and high complexity) × 4 (power magnitude of .2, .8, 1.4 and 2) MANOVA where performance and convergence were two outcome variables. Wilk's Lambda was significant for the main effect of power magnitude and two-way interactions of group size with power models and complexity ($p < .001$), but not for the three way interaction (p = n.s.).

The results indicated significant main effect of power size on performance and convergence ($F(3, 143928) = 5.56$, $p = .001$; $F(3, 143928) = 11.25$, $p < .001$), power size's two-way interactions with complexity ($F(6, 143928) = 4.66$, $p < .001$; $F(6, 143928) = 2.07$, $p < .1$;), and power model ($F(15, 143928) = 5.85$, $p < .001$; $F(15, 143928) = 8.48$, $p < .001$;) on performance and convergence respectively. The results are summarized in Figure 3 for low, moderate, and high complexity levels. We used only moderate complexity level for investigating the convergence since we did not find strong support for the interaction effect of complexity and power size, and three-way interactions were not significant.

For the exogenous power assignment case, there is observable performance difference between autocratic and egalitarian models only in low complexity condition. As the magnitude of high power decreases, the difference between power models disappears. Furthermore, bureaucratic model performs the least; however, it outperforms other in terms of convergence for moderate levels of power sizes. When power is endogenously assigned, meritocratic model outperforms others when there is a moderate and high power difference between low and high powered individuals. The relationship is reversed in terms of convergence. As in exogenous case, all models perform equally when the power size is low.

Discussion

Despite the high consensus over the importance of power, there exists less agreement on how to conceptualize power [13]. Inspired by the writings of early scholars on power, using Newtonian laws, this paper was able to conceptualize power simultaneously as a capacity, behaviors attached to this capacity, and realization of power in the form of influence.

Moreover, research on power has provided conflicting results in terms of level of power disparity and merit based assignment of power. We recognized that these discrepancies are due to the complexity of the phenomenon, and took an agent-based simulation approach where we compared the different power models categorized according to their level of disparity and appointment of power. Drawing upon literatures in functionalist theory of power and organizational design, this study brings forward further insights into the contradictory results in the literature. When power is appointed exogenously, the results of this paper add further evidence against the functionalist view and contribute to the growing literature in contingency theories of power [1]. We showed that for low levels of complexity egalitarian model yields better performance than the autocratic; however, for moderate high levels, this difference disappears. Furthermore, formal approaches in the organizational design note that a fully centralized hierarchy converges to a solution faster than a decentralized hierarchy in expense of lower

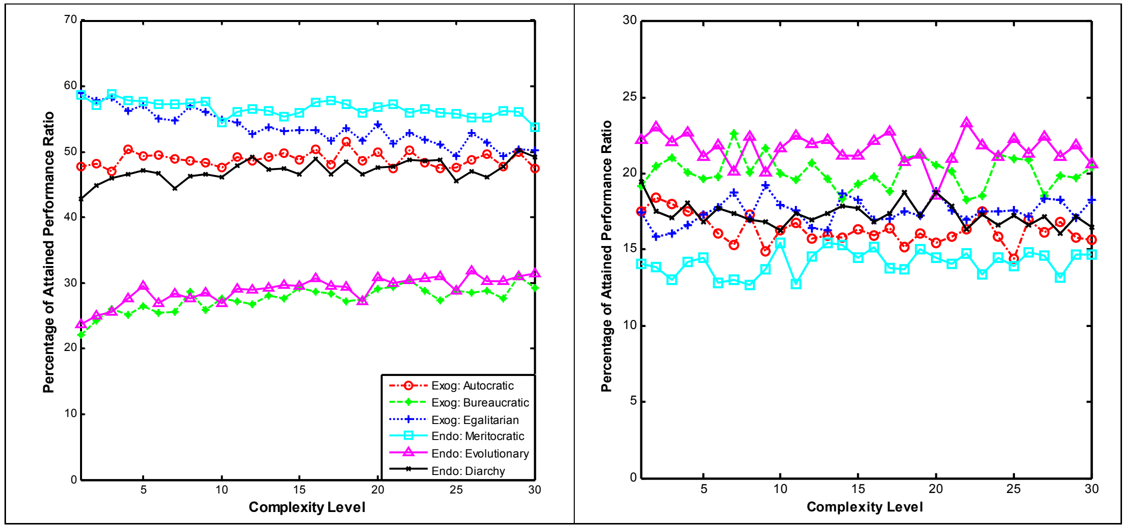

Figure 2: Comparison of Power Models in Terms of Performance (left) and Convergence (right)

Performance

a. Low Complexity b. Moderate Complexity c. High Complexity

Convergence

d. Moderate Complexity

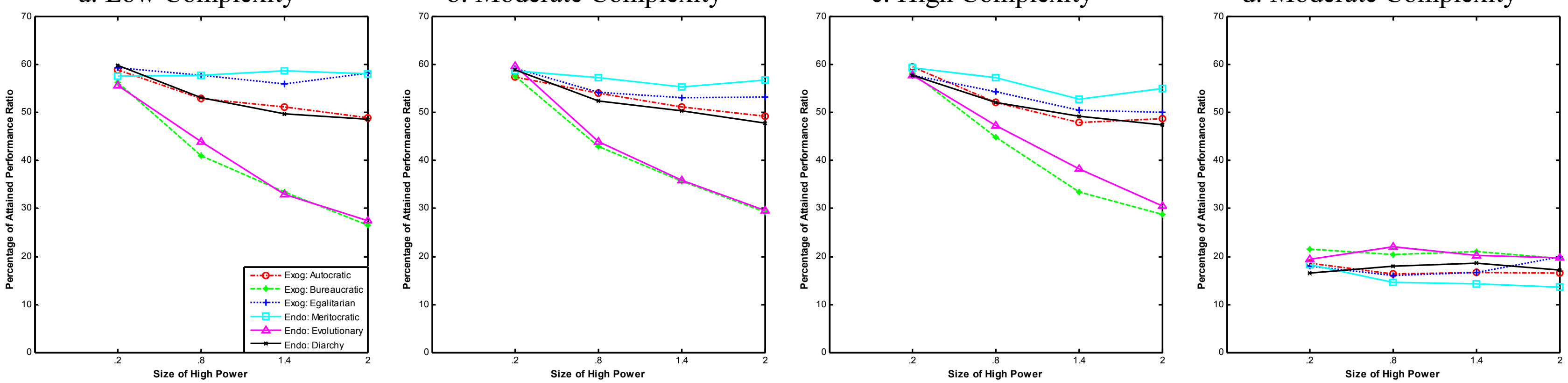

Figure 3: Comparison of Power Models with respect to Varying Sizes of High Powe

performance [20]. On the other hand, recently [17] showed that a decentralized hierarchy where decision making is delegated to the lowest levels in the hierarchy yields faster convergence as well as higher performance. In contrast to those studies considering power differences in terms of hierarchies, we found non-significant differences over power models with respect to complexity. These results call future research for further elaboration of the issue.

In addition to the stationary view of power, this study considers evolutionary dynamics of power assignment. The results suggest that assigning power to the most competent individual in each time period (meritocratic) yields higher performance compared to the evolutionary and diarchy power models. This result is in line with the functionalist arguments which propose that steeper hierarchies perform better if the most competent member has all the power. Moreover, our results show that assigning a portion of power to every group member according to their performance in the previous period provides quicker convergence to the solution, but least performance.

Overall, the results suggested that organizational design of power structures should consider both the level of power disparity level of disparity and evolutionary dynamics of power appointment. That is, high level of power disparity is desirable only when the power is assigned to the most competent group member in a dynamic setting. Low power disparity is desirable when power does not change from one period to another. Finally, this study highlights complexity level, and magnitude of high power as moderators in comparing different power models.

Limitations and Future Research

Given the fact that this study utilizes agent-based simulation tools for theory development, a natural limitation is the external validity of the findings. Inherent in this approach is the trade-off between parsimony and accuracy [6]. That is, the endeavor of crafting a complex phenomenon like power into a rather simple model may cause deviations from realism. For instance, we utilized laws of nature to analyze power which is a psychological and sociological issue. Therefore, empirical testing of the propositions of this study as well as the premise that the laws of Nature are applicable to organizations is essential in laboratory and field settings.

Future studies can extend the model in this paper in various directions. For instance, various network structures can be embedded in the group. The group interaction in our model assumes that once a higher performance level is reached, this level and its location is common knowledge. However, in an organization which is organized in prototypical pyramidal hierarchy, information from lower levels needs to move to the top until it reaches to the leader [1, 17, 21] which may cause delays and distortions in the information delivered. Additionally, the friction/speed of transmission is likely to differ between bottom-up and up-bottom information flows. Comparison of different power models can be investigated under different network structures varying in terms of their centrality of the leader where the speed of information flow is also manipulated.

Under these limitations, this paper was able to provide a multi-dimensional conceptualization of power, and to extend the formal design perspective where informal power structures and evolutionary dynamics were allowed in the group interaction. As a result, this study proposed further insights in discussion of power in the context of degree of disparity and endogenous assignment of power.

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