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1 **Ecological forces shape the individual cell proportions in microbial communities**

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8

9 **Abstract**

10 Microbial communities are indispensable for future biotechnology to produce valuable platform
11 chemicals and reduce the exploitation of fossil resources. Yet, the stability of microbial communities in
12 classical continuous reactor set ups is best brief or non-existent. This is due to ecological forces such as
13 stochastic and deterministic properties of communities that contribute to rapid changes in structure and
14 function to varying degrees. The review highlights the differences between these two properties, provides
15 tools for their estimation and gives an outlook on overcoming instabilities of microbial communities in
16 biotechnological reactor systems.

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25 Key words: microbial communities, single cell analysis, microbial flow cytometry, ecology of microbial
26 communities

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33 **Introduction**

34 Microbial communities are increasingly used as biocatalysts in biotechnological processes due to the
35 multifunctional properties of their members. In contrast to genetically engineered so-called superbugs,
36 which are engineered to perform the desired steps of a biochemical transformation as a pure culture,
37 microbial communities distribute the necessary transformation steps among different cell types. The
38 involvement of microbial communities in biotechnological production processes have at least two
39 advantages: One is that superbugs require expensive and specifically refined substrates to produce
40 valuable products. Instead, microbial communities can convert cheap complex materials from agriculture
41 and forestry as well as waste materials, which significantly reduces production costs. Such approaches
42 also lead to reduced use of fossil resources for the production of valuable chemicals and support the shift
43 to a circular economy. Second, the functional capacity in communities is vast, mostly redundant or
44 evolving, and thus offers a huge library of possible metabolic transformation pathways [1, 2]. But despite
45 these great benefits, there is a reluctance to use microbial communities more intensively in
46 biotechnology. With the exception of well-known processes such as biogas production, wastewater
47 treatment or the use of microbial communities in the food industry, there are no significant new
48 applications beyond these. In our opinion, the reason for this could be the inability to control complex
49 microbial communities in biotechnological processes. In this statement, we aim to identify the probable
50 causes of process instabilities caused by microbial communities as catalysts and pave the way for solutions
51 to overcome this problem.

52

53 **The ecology of microbial communities**

54 Ecological paradigms have not yet been considered in the control of biotechnological processes.

55 However, microbial communities are subject to ecological rules, just like any other population on earth,
56 e.g. the organisms of a forest or of a water body. Following macro-ecology theory, we seek to understand
57 the ecological mechanisms that govern the coexistence of microorganisms in biotechnologically exploited
58 communities.

59 Mostly, the biocatalysts themselves are not measured and evaluated as segregated values according to
60 their share and function, but rather treated as bulk biomass parameters. In addition, substrate turnover
61 and product synthesis are of interest, as well as abiotic operational parameters such as temperature, pH
62 and off-gas values, which are indispensable for conventional process control. This classical control scheme
63 originates from biotechnological processes, where the biocatalysts are pure populations with well-known
64 physiological properties. But already here the heterogeneity of the population contributed to unstable

65 processes and was therefore an issue in many studies [e.g., 3]. Triggers include cell cycle stages, age
66 distributions, plasmid copy numbers, or gene expression noise [4-8]. Of course, the degree of
67 heterogeneity is much higher in natural and also artificial communities, which affects the stability and
68 efficiency of the processes. To understand what drives assembly of and heterogeneity in microbial
69 communities, ecological theory can be of great help. The main ecological forces affecting the proportions
70 of cell types in communities are stochastic (neutral) and deterministic forces (Figure 1).

71

72 **Stochastic forces in biotechnological systems**

73 Stochastic behavior is an important ecological property that occurs in communities of any taxonomic level.
74 It assumes that members of a community share the same equivalence and fitness within a community,
75 which implies that they have the same prospects of reproduction and mortality [9]. Under this
76 assumption, deterministic factors like environmental parameters play no role in shaping communities,
77 because all individuals respond in the same way. Although this assumption is clearly counterintuitive to
78 our daily experience, most neutrality-based models provide reliable predictions [10, 11]. In ecology
79 theory, random birth and death of organisms are typical stochastic events. Moreover, systems governed
80 by stochastic forces exhibit intermediate frequencies, i.e., less extreme distributions of community
81 members, which behave therefore largely uniform with respect to each other. Interactions between
82 members of such communities are considered to be small.

83 We want to understand how these stochastic forces affect microbial communities in bioreactor systems
84 and how they can influence the efficiency of production processes. Typical bioreactors are stand-alone
85 systems operated in continuous cultivation modes. We do not consider batch systems here because
86 community lifetimes are limited in such systems (i.e., only a few generation times of contained organisms)
87 due to rapid onset of nutrient, carbon, and energy scarcity and rapid succession of harvesting steps, and
88 thus ecological forces have less influence. Instead, continuously operated bioreactor systems are
89 constantly fed with carbon and energy sources and contain a community that randomly loses community
90 members due to the dilution rate. This process can be considered as extinction (or cell death). In systems
91 with high stochasticity, there is high functional redundancy in otherwise taxonomically diverse
92 communities. Under these conditions, because cell types with similar functions are present in equal
93 abundance, different cell types with the same function can be easily interchanged. This inevitably leads
94 to structural changes in community composition. Therefore, functional redundancy is a major contributor
95 to changes in the dominance of particular cell types in a bioreactor, which leads to significant structural
96 instability [12-14]. Instability can be such that any given species becomes dominant because there are no

97 interactions among members of the community that would support a lasting dominance of a particular
98 cell type.

99 We also suspect that bioreactor systems operated at low cell densities are more prone to stochasticity.
100 The relative influence of coincidences such as random birth or death of a cell is greater in less dense
101 communities. Therefore, continuous cultivation systems with low cell densities containing a highly diverse
102 community with random functions are highly susceptible to stochastic events and to structural and
103 consequently functional instability.

104

105 **Deterministic forces in biotechnological systems**

106 Deterministic behavior is also an important ecological trait that occurs in communities at every taxonomic
107 level. Based on the concept of niche it assumes that members of a community are different from each
108 other, have different characteristics and functions within a community, and are often interdependent.
109 The two aspects of the niche concept relate either to the environmental needs of species ("requirement
110 niche") or to the impacts of species on their environment ("impact niche"), such as the consumption of
111 resources that leads to competition among species [15]. The competitive exclusion principle highlights
112 that a pair of species cannot stably coexist if they feed upon exactly the same resources under the same
113 environmental conditions [16]. Only species with different requirement niches are able to coexist, but
114 whether stable coexistence will be achieved depends on different impact niches. Both aspects indicate
115 that there are trade-offs between species to determine whether stability of a microbial community is
116 reached [17]. In multi-species systems of microbial communities, niche requirements can be highly
117 variable but also highly similar, so niche overlap cannot be avoided.

118 Considering again at the continuous cultivation mode, we can state that the dilution rate not only
119 promotes cell extinction as a stochastic feature, but also causes selection of cells with a reduced average
120 fitness difference. All cells with a growth rate below the dilution rate are lost, which over time leads to
121 selection of cells that grow equal to or faster than the dilution rate. Thus, the dilution rate contributes to
122 equalizing but not to stabilizing because the niche overlap is not reduced. The dilution rate can also be
123 considered as disturbance that favors faster-growing cells.

124 In macro-ecology theory, disturbances are called deterministic factors because they shape the
125 environment and communities. Deterministic factors, then, are those that have traditionally been used to
126 steer bioprocesses in desired directions. These are any operating parameters that help select specific cell
127 types through temperature and pH optima, through types of carbon sources and specific nutrient mixtures
128 or agitation rates. Strong deterministic features support interdependencies between cell types of

129 different requirement niches, such as when a substrate is used by one strain and the resulting
130 intermediate serves as a substrate for another strain to produce something. Interdependence lowers the
131 likelihood of monodominant communities with limited function and ensures continuous coexistence
132 among interconnected partners. In highly diverse communities, many such links may exist, but the
133 extinction of one of the partners may also lead to the extinction of the other. Unlike stochastically
134 controlled systems, the system is dominated especially by non-replaceable, abundant microorganisms.
135 Structural change is therefore less likely, while nesting, which describes the persistence of particular cell
136 types, is definitely high in deterministic systems [18, 19]. In high-density systems, only small, albeit
137 continuously provided, resources are available and they are therefore not susceptible to change. Overall,
138 deterministically organized systems appear to be more stable than those under the rule of stochasticity.

139

140 **Stochasticity vs. determinism**

141 Following the above reasoning, it can be assumed that setting up a bioreactor system in a way where only
142 deterministic forces act can lead to stability and also enable control. However, it is known from many
143 studies that stand-alone systems are almost never stable [12, 20], even though short-term stability is
144 sometimes reported. The rationale for these findings is that in any self-contained system involving living
145 organisms, stochasticity and determinism are simultaneously prevalent, and that in systems involving
146 multiple species, there will always be niche overlaps and uncertain impact niches which can be influenced
147 but never excluded. There are tools that make it possible to determine the proportion of one force or the
148 other, which can give an indication of the chance of setting a system further to the deterministic side for
149 control. However, there is a fundamental recognition that controlling communities in stand-alone
150 bioreactors appears to be impossible.

151

152 **Determination of stochastic and deterministic shares in microbial communities**

153 To determine the shares of deterministic and stochastic forces the measurement of the individual
154 organisms is necessary. Similar to counting and describing plants in a forest to understand active
155 ecological paradigms also microbial communities needs to be resolved to the individual cell level. This is
156 possible using microscopic technologies among them flow cytometry which allows a fast and cost effective
157 recording of dynamics in microbial community behavior. Microbial communities grown in bioreactors can
158 be routinely analysed according to abundancies of cell types over long periods of time using fingerprinting
159 approaches. Cell types are characterized related to cell size (forward scatter, FSC) and numbers of
160 chromosomes per cell (DNA fluorescence) or nucleic acid contents [21-24]. According to these

161 characteristics, cells are gathering as Gaussian distributions in subcommunities (SC). The changes in
162 numbers of SCs, the position of SCs in a 2D-plot and the numbers of cells per SC inform on community
163 dynamics over time (Figure 2). To determine the proportions of deterministic and stochastic forces in a
164 community, such information can be evaluated using the tool NST (Normalized Stochasticity Ratio; 25).
165 According to theory, the forces of determinism are the stronger the lower is the niche overlap and the
166 higher the niche impact (Figure 2). The niche impact is commonly estimated by correlation or network
167 analyses, with higher determinism indicated by tight correlations or compact networks (26; and only for
168 sequencing data, e.g. 27, 28). Other tools like QPEN and iCAMP use interspecies phylogenetic relationship
169 to estimate their similarity in niches [29, 30], however these methods also rely still only on sequencing
170 data.

171

172 **Outlook**

173 Multiple-species communities in stand-alone bioreactors would not be able to overcome stochastic forces
174 and create non-overlapping requirement niches and influence impact niches in ways that promote
175 coexistence. As a result, we will not be able to control such systems. And yet, there are system in the
176 environment that are stable over long periods of time, as can be observed in macro-ecology, but also in
177 certain connected basins of wastewater treatment plants and even in the microbiomes of human or
178 animal origin [31, 32]. The fundamental mechanism supporting this stability is dispersal. Recent data
179 indicate that the use of dispersal in loop designed continuous bioreactors greatly contributes to the
180 stability and synchrony of connected complex microbial communities [33]. This research is promising, but
181 more ideas and further consideration of ecological paradigms in biotechnological processes are needed
182 before implementation can be made possible. This may also require that new reactor designs be created
183 for stable and structurally and functionally controlled cultivation of microbial communities.

184

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279 This study addressed the stochastic changes and their avoidance in microbial community composition
280 under constant environmental conditions. Inspired by the mass effect paradigm in metacommunity
281 theory, the bioreactors were interconnected to allow different rates of looped mass transfer between
282 communities, which was proven to be effective in stabilization via the rescue effect.

283

284 **Figures**

285 Figure 1: Ecological forces shape the individual cell proportions in microbial communities. Blue: stochastic
286 forces and Orange: deterministic forces that are common in microbial communities that are cultivated in
287 continuous stand-alone bioreactors. These two forces have different influences on the structure and

288 function of communities and affect the productivity of biotechnological processes to varying degrees. (SC:
289 subcommunity)

290

291 Figure 2: Analyses of the type of ecological forces that shape the properties of microbial communities.

292 Cells are cultivated in continuous bioreactor systems and samples are taken within generation time and

293 analysed on the individual cell level by flow cytometry. Fingerprints per sample are generated and

294 dominant SCs are determined by cell abundance calculation. Networks and co-occurrences are visualized

295 by correlation analyses and proportions of stochastic and deterministic forces are calculated. (SC:

296 subcommunity)