Research Article

An Entropy-Based Formulation for Assessing the Complexity Level of a Mass Customization Industry 4.0 Environment

César Martínez-Olvera

Escuela de Negocios y Economía, Universidad de las Américas Puebla (UDLAP), Cholula, Mexico

Correspondence should be addressed to César Martínez-Olvera; cemarol@gmail.com

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It has been stated that Industry 4.0’s goal is, among others, the sustainable success in a market characterized by exigent and informed consumers demanding personalized products and services, where the level of manufacturing complexity increases with level of product customization. Even though different manufacturing complexity measures have been developed, there seems to be a lack of a comprehensive metric that address both the mass customization variety-induced complexity, and the complexity derived from the adoption of the Industry 4.0 paradigm. The main original contribution of this paper is the development of an entropy-based (entropic) formulation to address this last issue. Its validity and usefulness is put to the test via a discrete-event simulation study of a mass customization production system operating within an Industry 4.0 context. Our findings show that the entropic formulation acts as a fairly good trend indicator of the system’s performance parameter increase/decrease, but not as an estimator of the final values. A discussion of the managerial implications of the obtained results is offered at the end of the paper.

1. Introduction

The global dynamic competition impose manufacturing companies a series of business challenges such as operating with high levels of flexibility, efficiency, and adaptability in the face of product and process complexity [1], and to fast develop, design, and manufacture high quality, low cost, smart, mass customized products [2, 3], at a reasonable cost and with reduced energy and resources consumption [4]. In this scenario, the business survival demands the ability to react to rapid product changes through reconfigurability [5], via the intensive use of automation, computer systems, and software [6]. These are the main features related to Industry 4.0, a concept that is becoming much popular among organizations [7]. Industry 4.0 deals with the real time availability of all relevant information involved in the value creation process and the interconnection between human beings and machines [8–10]. This is carried out by combining manufacturing, automation, information, computing, communication, and control technologies, via the use of Internet of Things (IoT), Big Data, and cyber-physical system (CPS) associated technologies, in order to establish an interconnected industrial value creation process [11, 12]. This implies giving the customer the constant opportunity to become part of the value creation process through the development of tailored services [13]. It has been stated that Industry 4.0’s goal is—among others—the sustainable success in a market characterized by exigent and informed consumers demanding personalized products and services [14], that is, a mass customization market, where customers increase variant diversity [15], designed to their individual specifications [16, 17], and without paying a high price premium [18]. In simple terms, mass customization is a value chain-based manufacturing strategy [19] that aims to offer customized goods at low cost [20]. Within this context, there is a high level of uncertainty result of the variety of customer needs/preferences [21], which when viewed in terms of an increased number of components/parts, setups, and production processes is translated into a high level of manufacturing complexity [22], referred by [23, 24] as product variety-induced complexity. Moreover, the use of the Industry 4.0 potentialities is seen as an enabler of mass
customization [25], when considering that Industry 4.0 is a business-wide transformation—rather than a collection of technological projects—that allows a great potential for business value creation if information is properly exploited [26]. However, a collateral effect of the adoption of the Industry 4.0 initiative, for mass customization purposes, is the increase of the manufacturing system complexity [27], which in turn translates into a system efficiency decrease, mostly because of the involved big information and material flows [20]. Now, it has been mentioned that both production flexibility and information technology can provide the means to carry out mass customization [28, 29]:

(i) A common way to deal with mass customization issues (i.e., product variety-induced complexity) is production flexibility [30], as the use of a flexible manufacturing system can improve manufacturing performance, by reducing setup and manufacturing lead times [24, 31]

(ii) The smart components of Industry 4.0 can help reduce the complexity inherent to managing the mass-customization production system [32], via the use of information technologies [21], as long as there is no lack of information quality and availability for the use of these associated technologies [33]

Tjahjono et al. [9] mention that, in order for Industry 4.0 to truly achieve a sustainable success in a mass customization market, it is required to rapidly identify the customer needs, to simplify the customization process, and to assure—at no extra cost—the production system reconfigurability. This last fact has implications at the operational level as this requires the integration of the plug-and-produce, fully automated, digitized, and highly cost efficient CPS units [6]. For this reason, Section 1.1 reviews the topics of complexity and flexibility and their relationship with a Mass Customization Industry 4.0 environment (defined in this paper, as a mass customization production system operating within a reconfigurable CPS context). Derived from this literature review, the research features of this paper are defined, the research gaps and opportunities are identified, and the research goals—as well as the proposed research methodology to achieve them—highlighting the research originality, usefulness, and contributions are stated.

1.1. Literature Review. Complexity is considered to be a factor that influences productivity reduction [34]. According to [35, 36], there is a tradeoff between customization and complexity, where this last can be both good (required to customize products) and bad (failure by companies to address the tradeoff between the costs associated with customization). Sonsino et al. [37] talk about negative complexity, when referring to the probability decrease of choosing a “feasible” alternative (a product without incompatible components) as the complexity of that alternative increases. More specifically, References [24, 31, 38] claim that mass customization can both increase and decrease complexity. It is increased in the form of production program (i.e., planning and control), manufacturing (i.e., products’ diversity/variants), and configuration (i.e., information overload) complexity. It is decreased in the form of order taking process (i.e., product’s configurators), product (i.e., modular architectures), and inventory’s (i.e., customer, “pull” strategy) complexity. Now, according to [30, 39], major contributors to the complexity of a product and a system are the increasing number of components, variants, and changes. ElMaraghy and Urbanbici [40, 41] state that manufacturing process complexity is associated with the content (effort needed, i.e., number of stages or tools, to perform the task), quantity (quantity of information needed using entropy measurement), and diversity (ratio between the specific information needed for the task, to the total information) of information for a process. Regarding the role of information, Gullander et al. [30] claim that information flow creates both complexity and at the same time introduces possibilities of handling it, so an information support system is vital for the production system and needs to be considered as a parameter in relation to complexity. Now, several approaches have been developed for the quantification of complexity, mainly based on statistics, probabilities, and heuristics [42].

In this context, Shannon’s entropy-based information theory [43] has found a wide area of application as a measure of uncertainty. In example, Breithaupt [44] developed an analytical model for quantitatively measuring the system complexity—due to different part routings, processing times, and mix ratios—of a manufacturing system, using information entropy. ElMaraghy et al. [45] defined a code-based structural complexity index. Suh [46] successfully adopted complexity in the context of a system design, in achieving functional or design requirements. Zhu et al. [47] applied the information entropy to complexity model generation on the level of station and system at mixed-model assembly systems. Smart et al. [48] extended the information-based measures to the dynamic measurements of the systems. Sonmez and Koç [49] offer an entropy-based evaluation for the quantification of the overall manufacturing complexity, which takes into account the type of machinery, number and type of operations, and routing for each product. Soltysova and Bednar and Modrak et al. [31, 50] offer an extensive review of the complexity concept in the manufacturing arena.

Regarding the manufacturing complexity measure issue, Arteta and Giachetti [51] state that different measures have been developed over the years, i.e., manufacturing complexity measure [51–54]; operational complexity [55]; structural complexity index [56]; internal static manufacturing complexity measure [57]; and static/dynamic complexity [58–60]. Specific examples about the approaches used for measuring structural complexity of manufacturing systems can be found in [23, 42, 60, 62]. For a complete review of entropy-based measures for manufacturing complexity quantification, the readers should consult [63–66]. Now, even though the previous work suggests the product, process, and resources elements (or information categories) as necessary to describe a manufacturing system’s complexity, there seems to be a lack of a comprehensive metric that combines both the amount and type of information needed to describe a system’s complexity [56].
Regarding the issue of mass customization variety-induced complexity, the current manufacturing complexity metrics do not reflect the true aspect of this last [24], and quantification approaches that investigate how the adoption of the Industry 4.0 paradigm increases its complexity are limited [27]. Some of the work in this venue includes Nielsen and Brunoe [67], who proposed two indexes to measure the level of mass customization, namely, the differentiation point index and the setup index, which take into account elements like number of different manufacturing processes, number of different manufactured varieties, average throughput time, number of setup, and related costs. Mourtzis et al. [68, 69] proposed an entropic measure to quantify the complexity before and after shifting from a traditional manufacturing system into a Manufacturing 4.0 manufacturing system. Mourtzis et al. [27] propose a metric for the quantification of customization complexity, from an Industry 4.0 point of view, taking into account the quantity of the information managed, the diversity/variants of the exchanged information, and the content of the messages that transfers the information (the premise is that the increase in any of these elements increases the system’s complexity significantly). Martinez-Olvera and Mora-Vargas [70] develops the system dynamics model of the mass customization paradigm and use it to study the effect the level of flexibility has on the level of fulfilled demand.

Regarding the role of flexibility: a key mass customization capability—understood this last as a bundle of routines and resources that contribute to performance [71]—is process flexibility [72]. In this case, two fundamental flexibility requirements for mass customization production systems are product mix, ability adapt, and produce to diverse customer requirements; and changeover flexibility, ability to switch between different products and/or components in a fast-paced and cost-efficient manner [22]. Bellemare [73] refers to these as flexibility and changeability—critical enablers for efficient mass customization [74]—as they allow the runtime capabilities such as fast and easy reconfiguration of production facilities, that without them, product variability and customization would result in tremendous increase of production costs [75]. However, the higher flexibility a system has, the more difficult it is to achieve high efficiency, an issue that can be properly addressed by the use of automation that can improve manufacturing productivity and efficiency, but contributing the system complexity, as they are highly integrated with the products, processes, information, resources, human, tasks, and organization [30]. For this reason, it is that an enterprise competing within a mass customization Industry 4.0 environment depends on the manufacturing efficiency of the transforming processes [16, 17, 27].

1.2. Research Features. The previous sections can be summarized as follows: mass customization production systems exhibit product variety-induced complexity, which it is increased when operating within an Industry 4.0 context. Flexibility can help reducing the level of complexity, but at the same time, it makes difficult achieving high levels of efficiency. This presents a potential problem for an Industry 4.0 mass customization environment, as it depends—for its successful operation—on the manufacturing efficiency of the transforming processes. Now, from the presented literature review (see Table 1) the following research gaps and opportunities are defined:

1. Current manufacturing complexity metrics do not reflect the variety-induced complexity of mass customization [24]
2. The quantification of the complexity increases due to the adoption of the Industry 4.0 paradigm—more specifically, due to resources reconfigurability—is limited [27]

As a first step into the development of a comprehensive metric that covers both sources of complexity, this research effort proposes an exploratory approach, with its main goal being addressing the possibility of using an entropic formulation for assessing the complexity level of a Mass Customization Industry 4.0 environment (known henceforth as the $\beta_{MC4.0}$ expression). The originality of the $\beta_{MC4.0}$ expression comes from its predictive and constructive validity. The predictive validity refers to the ability to "predict" a theorized outcome, which is provided by following an entropy-based approach, as suggested by Reference [56]. The construct validity refers to the formality of the development process, which is based on previous published work by the author [76, 77], where an entropy-based metric of a product's BOM blocking effect is derived. The usefulness of the $\beta_{MC4.0}$ expression is demonstrated via the use of a discrete-event simulation model of a mass customization production system operating within an Industry 4.0 environment. The rest of the paper is organized as follows: Section 2 presents the case of a mass customization production system, upon which, a discrete-event simulation model is built, with the idea of generating statistical output that reflects the behavior of the system. Based on these results, Sections 3 presents the theory foundation of the $\beta_{MC4.0}$ expression, where Section 4 adds the Industry 4.0 complexity component—in the form of flexibility through the system reconfigurability—and put to the test the validity of the $\beta_{MC4.0}$ expression. Derived from the obtained results, Section 5 presents the final conclusions and the identified future research venues.

2. The Mass Customization Production System

According to [31], the mass customization paradigm involves a design-sell-make-assemble cycle. Dean et al. and Daaboul et al. [78–80] put this cycle into six fundamental processes, while Latorre-Biel et al. [14] establishes a five step sequence for the execution of the mass customization approach, within an Industry 4.0 environment:

1. Customers personalize their purchase through a website or mobile application software
2. The purchasing information is sent directly to the production line not requiring a fabrication order from a management level of decision
Table 1: Literature review summarizing table.

| Topic addressed                  | References               |
|----------------------------------|--------------------------|
| Good/bad/negative complexity     | [35–37]                  |
| Complexity increase/decrease     | [24, 31, 38]             |
| Complexity and information flow  | [30]                     |
| Product complexity               | [30, 39]                 |
| Complexity quantification        | [42–48]                  |
| Manufacturing process complexity | [23, 31, 40–42, 49–54, 61, 62] |
| Operational/structural/internal  | [55–57]                  |
| Complexity entropy-based measures| [58–60, 63–66]           |
| Mass customization measurement   | [24, 27, 67]             |
| Mass customization and complexity| [27, 68, 69]             |
| Mass customization and flexibility| [22, 72–75]             |
| Flexibility and complexity       | [30]                     |

(3) The purchased product is associated to a sequence of services required during its manufacturing process (fabrication list)

(4) Each product requests services (via IoT) to one or several machines with the purpose of manufacturing the final product

(5) Once all services are completed, the product is packed and delivered

The mass customization production system proposed in this research effort focuses only on steps 3 and 4 of the previous list. It is theoretical in nature—similar to the one presented in Bednar et al. [81], where a mass customized assembly uses three stable and two optional components resulting in four complete product configurations—and complies with the set of mass customization configuration attributes presented in Martínez-Olvera and Mora-Vargas [70]. The set of products to be processed by this production system is presented in Figure 1, and Table 2 shows the manufacturing process routes for each of these products, in terms of type of manufacturing resource used (Figure 2) and processing time (i.e., product 1B uses manufacturing resource $M_1$ for three time units, followed by the use of manufacturing resource $M_4$ for three time units).

2.1. Simulation Model. The discrete-event simulation (DES) model of the mass customization production system was build following an approach similar to the one presented in Raza et al. [20], where the impact of introducing the Industry 4.0 paradigm within a Mass Customization environment is studied. This DES model was developed in ARENA [82] and used to generate statistical output regarding its performance (measured in terms of the manufacturing resources’ queue length, and the products’ waiting time). The logic behind the DES model was implemented based on the structure of the model “A Small Manufacturing System,” presented in [82], specifically with the use of the STATION and ROUTE modules. Figure 3 presents an excerpt of the DES model, for the case of manufacturing resource $M_1$. The simulation run output was verified and validated according to the recommendations proposed by Hwarng et al. [83]. The trace and debugging functions were used to check the logic of the activities an entity encounters in the system, and the DES model output was examined for reasonableness by setting the processing times to some known deterministic value and compared with manual calculations (finding no discrepancies between the simulation and manual results). In this case, the DES model can be considered as a research instrument for theory testing [84] rather than for theory development [85]. A simulation run time, long enough to allow the total processing of twelve units of each product type, was used. The mass customization production system is assumed to be operating continuously, i.e., breakdowns, changeover, setup, and load/unload times are assumed to be negligible, and each manufacturing resource is capable of processing only one unit at a time. All the manufacturing resources were subject to certain degree of variation (reflected as an exponential normal distribution for the processing times). Thirty replications were used in order to avoid significant variation in the observed results. Confidence intervals of 90% were used in order to provide the proper statistical basis for making inferences and conclusions. Ten different scenarios were tested under these operative conditions (Table 3).

2.2. Simulation Results. Table 4 shows the simulation results of the ten tested scenarios (Table 3), for each of the four manufacturing resources (i.e., Machines $M_1$, $M_2$, $M_3$, and $M_4$, Figure 2), in terms of waiting time ($W_t$, minutes) and queue length ($L_q$, number of units). Figures 4(a) through 4(d) shows the normalized values of Table 4, where in each case Series 1 (solid line) refers to $W_t$ and Series 2 (short dotted-double line) refers to $L_q$. It can be observed that the behavior of both $W_t$ and $L_q$ follows a similar trend, where for the case of $M_1$ and $M_4$, both trend lines are almost superposed. Section 3 focuses on deriving the $\beta\epsilon_{MC4.0}$ expression, capable of resembling the observed behavior of the system.

3. Theory Foundation of the $\beta\epsilon_{MC4.0}$ Expression

At this point, it must be noted that, in order for the $\beta\epsilon_{MC4.0}$ expression to truly represent the manufacturing complexity of a mass customization production system operating within an Industry 4.0 environment, the complexity contribution of the product, process, and resources elements must be taken into account. These elements refer to:

(i) Product: the different number of manufactured products, the number of number of corresponding components and functions, and the overall products’ mix ratio

(ii) Process: the different routings for each product and the corresponding processing times

(iii) Resources: the different types of machinery, number and type of operations capable of performing, and number of required setups
Now, Martínez-Olvera explained in his work of [76] (equation (1)) and [77] (equation (2)) why formulations such as the ones presented by [58, 86] need to be modified in order to reflect the impact the BOM structure has on the process flow. In a similar way, equations (1) and (2) must be adapted in order to reflect the manufacturing complexity contribution to the mass customization production system operating within an Industry 4.0 environment:

\[
\beta_{\text{NB}} = \frac{1}{(1/P_{\text{NB}}) \cdot \log 2 (1/P_{\text{NB}})}, \tag{1}
\]

\[
\beta_{\text{NB}} = \left[ \frac{1}{P_{X}} \right] \cdot \log 2 \left[ \frac{1}{1 - P_{\text{NB}}Y} \right] \cdot P_{\text{NB}}Y. \tag{2}
\]

For this matter, both equations (1) and (2) were manipulated for different combinations of the $P \log_2 P$ expression, i.e., $P \log_2 P, P \log_2 (1/P), (1/P) \log_2 P, (1/P) \log_2 (1/P),$ and $1/[(1/P) \log 2 (1/P)]$, until one combination resembled the observed behavior of the system (Figures 4(a) through 4(d)). In this case, the $\beta_{\text{MC4.0}}$ expression took the form of

\[
\beta_{\text{MC4.0}} = \left( \frac{1}{P} \right) \cdot \log 2 \left( \frac{1}{P} \right). \tag{3}
\]

where $P_i$ is calculated as shown in Table 5 (for the case of manufacturing resource $M_1$, Table 5). It must be noted that whenever a product processing time on $M_1$ appears as NA, its contribution to $\beta_{\text{MC4.0}}$ expression value is considered to be negligible. Now, the term $\Sigma$ processing time is the accumulated time for each tested scenario (Table 3). In this way, $\Sigma$ processing time for scenario $7 = 10$ and is the result of adding up the processing time of product 1 up to product 7 (i.e., $0 + 0 + 2 + 2 + 1 + 3 = 10$). Plugging these probabilities $P_i$ into the $\beta_{\text{MC4.0}}$ expression, the values shown in Table 6 are obtained. Appendix at the end of this document shows more details of the mechanics of these calculations.

![Figure 1: Set of products processed by the mass customization production system.](image-url)

| Product number | Product type  | Manufacturing process routes                  |
|----------------|--------------|-----------------------------------------------|
| 1              | 1B           | $3M_2 + 3M_4$                                 |
| 2              | 1C           | $4M_3 + 4M_4$                                 |
| 3              | 2AB          | $2M_1 + 2M_2 + 2M_4$                          |
| 4              | 2AC          | $2M_1 + 4M_3 + 6M_4$                          |
| 5              | 2A1B1C       | $2M_1 + 1M_2 + 2M_3 + 5M_4$                   |
| 6              | 1A2B1C       | $1M_1 + 2M_2 + 2M_3 + 7M_4$                   |
| 7              | 3AB          | $3M_1 + 3M_2 + 6M_4$                          |
| 8              | 3AC          | $3M_1 + 6M_3 + 9M_4$                          |
| 9              | 3A1B2C       | $3M_1 + 1M_2 + 4M_3 + 8M_4$                   |
| 10             | 2A3B1C       | $2M_1 + 3M_2 + 2M_3 + 9M_4$                   |

![Table 2: Manufacturing process routes.](table-url)
Manufacturing process (one unit):
1\text{M}_1 + 1\text{M}_2 + 4\text{M}_3 + 8\text{M}_4

Manufacturing resources:
\text{M}_1, \text{M}_2, \text{M}_3, \text{M}_4

System's reconfiguration level

Manufacturing process (one unit):
9\text{M}_{14} + 5\text{M}_{23}

Manufacturing resources:
\text{M}_{14}, \text{M}_{23}

Figure 2: Types of manufacturing resources used by the mass customization production system.

Figure 3: Excerpt of the DES model, manufacturing resource \text{M}_1 case.

Table 3: Tested scenarios.

| Scenario number | Product type processed | Simulation run time (min) | Number of units produced |
|-----------------|------------------------|---------------------------|--------------------------|
| 1               | 1B                     | 60                        | 12                       |
| 2               | 1B, 1C                 | 110                       | 24                       |
| 3               | 1B, 1C, 2AB            | 140                       | 36                       |
| 4               | 1B, 1C, 2AB, 2AC       | 210                       | 48                       |
| 5               | 1B, 1C, 2AB, 2AC, 2A1B1C | 230                      | 60                       |
| 6               | 1B, 1C, 2AB, 2AC, 2A1B1C, 1A2B1C | 370                      | 72                       |
| 7               | 1B, 1C, 2AB, 2AC, 2A1B1C, 1A2B1C, 3AB, | 380                      | 84                       |
| 8               | 1B, 1C, 2AB, 2AC, 2A1B1C, 1A2B1C, 3AB, 3AC | 530                      | 96                       |
| 9               | 1B, 1C, 2AB, 2AC, 2A1B1C, 1A2B1C, 3AB, 3AC, 3A1B2C | 630                      | 108                      |
| 10              | 1B, 1C, 2AB, 2AC, 2A1B1C, 1A2B1C, 3AB, 3AC, 3A1B2C, 2A3B1C | 650                      | 120                      |

Table 4: Simulation results for all the manufacturing resources \text{M}_i.

| Manufacturing resource \text{M}_i | Performance measure | Scenario number |
|-----------------------------------|---------------------|-----------------|
|                                   | \text{W}_t         | 1    2    3    4    5    6    7    8    9    10 |
| \text{M}_1                         | 0.000342 0.000342 0.000342 0.000342 0.000342 0.000342 0.000342 0.000342 0.000342 0.000342 |
| \text{M}_2                         | 0.000342 0.000342 0.000342 0.000342 0.000342 0.000342 0.000342 0.000342 0.000342 0.000342 |
| \text{M}_3                         | 0.000342 0.000342 0.000342 0.000342 0.000342 0.000342 0.000342 0.000342 0.000342 0.000342 |
| \text{M}_4                         | 0.000342 0.000342 0.000342 0.000342 0.000342 0.000342 0.000342 0.000342 0.000342 0.000342 |
Table 7 shows the $\beta_{\text{MC}4.0}$ expression values for all the rest of the manufacturing resources $M_i$. Figures 5(a) through 5(d) show the normalized values of Table 7 (Series 3, long dotted-double line), where again, in each case Series 1 (solid line) refers to $W_t$ and Series 2 (short dotted-double line) refers to $L_q$. It can be observed that the normalized values of the $\beta_{\text{MC}4.0}$ expression follow the trend of the normalized values of $W_t$ and $L_q$, where in some cases (i.e., $M_3$ and $M_4$) this following is really close. A look to the accumulated workload per manufacturing resource $M_i$ (shown in Table 8) reveals that it is precisely these two manufacturing resources that are the ones exhibiting the highest values (20.68% and 50.86%, respectively), leading us to think that there is a relationship between the accuracy of the $\beta_{\text{MC}4.0}$ expression and the level of workload of a manufacturing resource $M_i$. So up to this point, the $\beta_{\text{MC}4.0}$ expression acts as a fairly good trend indicator of the system’s performance parameters increase/decrease, but not as an estimator of the final values. This conclusion is consistent with the previous reported findings, i.e., [76, 77].

Now, before proceeding to Section 4, a couple of things must be mentioned. According to [87], the “what,” “where,” and “how” of a production process is known as the execution function, which depends on the relatively static physical configuration of the production system. On the other hand, the “what,” “where,” and “when” is known as the

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**Table 5: Probabilities $P_i$ for all the ten tested scenarios.**

| Product number | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 |
|----------------|---|---|---|---|---|---|---|---|---|----|
| Processing time on $M_i$ (from Table 2) | NA | NA | 2 | 2 | 2 | 2 | 1 | 3 | 3 | 3 |
| $\Sigma$ processing time | 0 | 0 | 2 | 4 | 6 | 7 | 10 | 13 | 16 | 18 |
| $P_1$ | NA | NA | NA | NA | NA | NA | NA | NA | NA | NA |
| $P_2$ | NA | NA | NA | NA | NA | NA | NA | NA | NA | NA |
| $P_3$ | 1 | 0.5 | 0.333 | 0.285 | 0.2 | 0.153 | 0.125 | 0.111 |
| $P_4$ | 0.5 | 0.333 | 0.285 | 0.2 | 0.153 | 0.125 | 0.111 |
| $P_5$ | 0.333 | 0.285 | 0.2 | 0.153 | 0.125 | 0.111 |
| $P_6$ | 0.142 | 0.142 | 0.0769 | 0.0625 | 0.0555 | 0.0555 |
| $P_7$ | 0.3 | 0.230 | 0.187 | 0.166 |
| $P_8$ | 0.187 | 0.187 | 0.166 |
| $P_9$ | 0.111 |
| $P_{10}$ | 0.111 |
| Scenario number | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 |
Table 6: $\beta_{\text{MC4.0}}$ values for manufacturing resource $M_i$.

| Scenario number | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 |
|-----------------|---|---|---|---|---|---|---|---|---|----|
| $P_1$           | NA| NA| NA| NA| NA| NA| NA| NA| NA| NA |
| $P_2$           | NA| NA| NA| NA| NA| NA| NA| NA| NA| NA |
| $P_3$           | 0 | 2 | 4.754 | 6.325 | 11.609 | 17.552 | 24 | 28.529 |
| $P_4$           | 2 | 4.754 | 6.325 | 11.609 | 17.552 | 24 | 28.529 |
| $P_5$           | 4.754 | 6.325 | 11.609 | 17.552 | 24 | 28.529 |
| $P_6$           | 19.651 | 33.219 | 48.105 | 64 | 75.058 |
| $P_7$           | 5.798 | 9.167 | 12.880 | 15.509 |
| $P_8$           | 5.789 | 9.167 | 12.880 | 15.509 |
| $P_9$           | 12.880 | 15.509 |
| $P_{10}$        | 28.529 |
| $\beta_{\text{MC4.0}}$ | NA| NA| 0 | 4 | 14.264 | 38.628 | 73.838 | 119.098 | 174.6406 | 235.705 |

Table 7: $\beta_{\text{MC4.0}}$ values for all the manufacturing resources $M_i$.

| Manufacturing resource type | $\beta_{\text{MC4.0}}$ value | Scenario number |
|-----------------------------|-------------------------------|-----------------|
| $M_1$                       | Actual                        | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 |
|                             | Normalized                    | NA| NA| NA| NA| 0.016| 0.0605| 0.163| 0.313| 0.505| 0.7409| 1|
| $M_2$                       | Actual                        | 0 | 0 | 4.533 | 4.533 | 22.264 | 43.773 | 78.853 | 78.853 | 133.0586 | 195.638 |
|                             | Normalized                    | 0 | 0 | 0.0231 | 0.0231 | 0.113 | 0.223 | 0.403 | 0.403 | 0.6801 | 1|
| $M_3$                       | Actual                        | 0 | 0 | 0 | 4 | 18.219 | 40.529 | 40.529 | 81.342 | 123.561 | 183.587 |
|                             | Normalized                    | 0 | 0 | 0 | 0.0217 | 0.0992 | 0.2207 | 0.2207 | 0.443 | 0.673 | 1|
| $M_4$                       | Actual                        | 0 | 4.265 | 17.151 | 43.866 | 76.865 | 128.2303 | 185.4705 | 272.136 | 364.0225 | 475.45 |
|                             | Normalized                    | 0 | 0.0089 | 0.036 | 0.0922 | 0.161 | 0.269 | 0.39009 | 0.572 | 0.765 | 1|

Figure 5: (a) $M_1\beta_{\text{MC4.0}}$ value behavior; (b) $M_2\beta_{\text{MC4.0}}$ value behavior; (c) $M_3\beta_{\text{MC4.0}}$ value behavior; (d) $M_4\beta_{\text{MC4.0}}$ value behavior.
decision-making function, which depends on the relatively dynamic physical configuration of the production system (due to the presence of alternative manufacturing resources). In this case, the $\beta_{MC4.0}$ expression (as developed so far) only reflects the “execution” part of the mass customization production system, as the manufacturing process for all the ten products is always the same. Section 4 tests the validity of the $\beta_{MC4.0}$ expression for the “decision-making” part, as the Industry 4.0 complexity component (in the form of manufacturing resources flexibility) is added to the operation of the mass customization production system.

4. Adding the Industry 4.0 Complexity Component

Among the main pillars of Industry 4.0 mentioned by [88]

(1) Smart products: the product itself requests the required resources and orchestrates the production processes for its completion.

(2) Smart machines; machines can self-organize within the production network to orchestrate the production processes for its completion; therefore, it becomes a matter of interest to test the validity of the $\beta_{MC4.0}$ expression when these operation modes are added to the mass customization production system. More specifically, now there are two new types of manufacturing resources (i.e., $M_{14}$ and $M_{23}$, as shown in Figure 2) within the mass customization production system. Because of this last, now each product has a “variable” manufacturing process, which changes dynamically, depending on the operation mode of the production system. In this way,

(a) Pillar #1, product-to-product operation mode (Figure 6(a)): products “talk” to each other and decide which one is processed next by a certain manufacturing resource

(b) Pillar #2, machine-to-machine operation mode (Figure 6(b)): manufacturing resources “talk” to each other and decide which product is processed next by each one of them

Figure 6(a) refers to the product-to-product operation mode, where products trade place depending on which type of manufacturing resource is free. For example, $M_{23}$ is free and can fulfill 50% of the manufacturing process of Product 2A1B1C (and because of this Product 1B trades its first place on the waiting queue). In the case of Figure 6(b), the machine-to-machine operation mode, each manufacturing resource drag to its waiting queue the type of product that is more convenient to be processed next. For example, $M_{23}$ drags Product 2A1B1C from $M_2$ waiting queue (for the same reason expressed above) and $M_2$ proceeds in a similar way (dragging Product 1B from $M_{23}$ waiting queue). In this way—as a first step in this research line—it becomes necessary to adapt the discrete-event simulation model (described in Section 2.1) in order to reflect the product-to-product operation mode (leaving the machine-to-machine operation mode for future research, mainly to not overextend the length of this research document), use the same operative conditions of the ten tested scenarios (presented in Section 2.1), and arbitrarily assigning products 5 and 6 priority of use of manufacturing resources $M_{14}$ and $M_{23}$, respectively. The logic behind the product-to-product operation mode was implemented based on the structure of the model “Service Model with Balking and Reneging,” presented in Reference [82], specifically with the use of the SEARCH and REMOVE modules. Figure 7 presents an excerpt of the DES model, for the case of manufacturing resource $M_{1}$ and $M_{14}$.

Now, regarding the calculation of the probabilities $P_i$ (used in equation (3)), as these depend upon the processing time of each product’s manufacturing process route—which now varies due to the fact that there are multiple alternative manufacturing process routes (result of including machines $M_{14}$ and $M_{23}$)—there is a need of making an adjustment to the calculation of $P_i$. Table 9 presents all the alternative manufacturing process routes each product can follow, the frequency on which these routes are followed (for this matter, the number of simulations replications was varied until no significant variation in the frequency was observed), and the impact of these frequencies have on the corresponding processing times of each product (Appendix at the end of this document shows the calculations that verify the
Figure 7: Excerpt of the DES model, manufacturing resource $M_1$ and $M_{14}$ case.

Figure 6: (a) Product-to-product operation mode. (b) Machine-to-machine operation mode.
validity of these values. In this way, the processing times on $M_1$—presented on Table 5 (second row)—become the processing times, as shown in Table 10 (second row), and the calculation of $P_1$ is performed as established previously.

| %  | $P_1$ | $P_2$ | %  | $P_3$ | $P_4$ |
|----|-------|-------|----|-------|-------|
| $M_1$ | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| $M_2$ | 1.587 | 0.087 | 0.000 | 0.000 | 0.000 |
| $M_3$ | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| $M_4$ | 1.587 | 0.000 | 1.240 | 0.000 | 0.000 |
| $M_5$ | 0.000 | 0.087 | 0.000 | 0.000 | 0.000 |
| $M_6$ | 0.000 | 0.000 | 1.240 | 0.000 | 0.000 |
| $M_7$ | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| $M_8$ | 1.587 | 0.000 | 0.000 | 0.000 | 0.000 |
| $M_9$ | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| $M_{10}$ | 2.827 | 1.327 | 3.417 | 3.708 | 0.292 |
| $M_{11}$ | 0.000 | 0.000 | 0.583 | 0.000 | 0.000 |
| $M_{12}$ | 0.173 | 1.327 | 0.292 | 0.583 | 0.000 |

Table 9: Alternative manufacturing process routes, frequency, and processing time impact.

| %  | $P_1$ | $P_2$ | %  | $P_3$ | $P_4$ |
|----|-------|-------|----|-------|-------|
| $M_1$ | 0.391 | 0.058 | 0.072 | 0.000 | 0.000 |
| $M_2$ | 0.783 | 0.116 | 0.145 | 0.000 | 0.000 |
| $M_3$ | 0.391 | 0.058 | 0.072 | 0.000 | 0.000 |
| $M_4$ | 0.783 | 0.116 | 0.000 | 0.000 | 0.000 |
| $M_5$ | 1.957 | 0.000 | 0.000 | 0.000 | 0.000 |
| $M_6$ | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| $M_7$ | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| $M_8$ | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| $M_9$ | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| $M_{10}$ | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| $M_{11}$ | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| $M_{12}$ | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |

Table 10: Processing times on $M_1$, product-to-product operation mode.

| Product number | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 |
|----------------|---|---|---|---|---|---|---|---|---|----|
| Processing time on $M_1$ (from Table 8) | NA | NA | 1.456 | 1.403 | 1.884 | 0.567 | 2.118 | 2.526 | 2.069 | 1.647 |
| Scenario number | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 |

Appendix at the end of this document shows more into details the mechanics of the calculations that verify the validity of the values, as shown in Table 9. Table 11 shows the simulation results of the new ten tested scenarios and each of
Table 12: Simulation results for all the manufacturing resources $M_i$, product-to-product operation mode.

| Manufacturing resource type | Performance measure | Scenario number |
|-----------------------------|----------------------|-----------------|
| $M_1$                        | $W_t$                | 1 2 3 4 5 6 7 8 9 10 |
|                             | $L_q$                | 0.068015 0.00733 0.00278 0.03243 0.15273 0.86573 0.94587 1.36474 1.63628 7.7899 |
| $M_2$                        | $W_t$                | 0 0 4.770 4.770 21.81 44.32 80.09 80.09 95.13 99.86 |
|                             | $L_q$                | 0 0 0.0621 0.7718 0.9608 1.6419 3.0547 2.5648 2.803 3.6526 4.3138 |
| $M_3$                        | $W_t$                | 0 1.056 7.427 9.65 10.14 23.03 23.40 28.40 25.47 34.66 |
|                             | $L_q$                | 0 0 0.0621 0.7718 0.9608 1.6419 3.0547 2.5648 2.803 3.6526 4.3138 |
| $M_4$                        | $W_t$                | 6.5205 8.224 19.513 55.755 74.968 89.057 95.133 18.025 18.640 23.011 |
|                             | $L_q$                | 1.853 7.346 14.119 15.147 17.73 18.025 18.640 23.011 27.721 21.4296 |
| $M_{14}$                     | $W_t$                | 0 0 0.6261 2.910 3.375 4.741 5.171 8.619 8.956 12.569 |
|                             | $L_q$                | 0 0 0.0621 0.7718 0.9608 1.6419 3.0547 2.5648 2.803 3.6526 4.3138 |
| $M_{23}$                     | $W_t$                | 0.016 0.024 0.064 0.127 0.155 0.227 0.444 0.680 1.729 2.183 |
|                             | $L_q$                | 0 0 0.0621 0.7718 0.9608 1.6419 3.0547 2.5648 2.803 3.6526 4.3138 |

(a) Series 1
(b) Series 2
(c) Series 3

Figure 8: Continued.
the six manufacturing resources (original machines \(M_1, M_2, M_3,\) and \(M_4\) plus the new \(M_{14}\) and \(M_{23}\)), while Table 12 shows the respective \(\beta_{\text{MC4.0}}\) values, and Figures 8(a) through 8(f) show the normalized values presented on Tables 11 and 12. In this case, \(W_t\) is Series 1 (solid line), \(L_q\) is Series 2 (short dotted-double line), and \(\beta_{\text{MC4.0}}\) is Series 3 (long dotted-double line). Once again, the normalized values of the \(\beta_{\text{MC4.0}}\) expression follow the trend of the normalized values of \(W_t\) and \(L_q\). However, an analysis similar to the one presented on Table 13 reveals that, in this case, the really close trend following occurs for the alternative, and more flexible, manufacturing resources \(M_{14}\) and \(M_{23}\) (which by the way are not necessarily the manufacturing resources \(M_i\) with the highest accumulated workload. See values in Table 13, *cursive letters*).

If the accuracy of the \(\beta_{\text{MC4.0}}\) expression is related to the level of workload of a manufacturing resource \(M_i\), an explanation for these results lies in (1) the fact that these two manufacturing resources (that is, \(M_{14}\) and \(M_{23}\)) split the workload of manufacturing resources \(M_4\) and \(M_3\), respectively, and (2) the fact that these two manufacturing resources (that is, \(M_{14}\) and \(M_{23}\)) have priority of use for some of the products. Table 13 shows how the workload is split, by comparing the values of Table 13, *cursive letters*, and Table 10 (bold letters). These results lead us to conclude that up to this point, the \(\beta_{\text{MC4.0}}\) expression acts as a fairly good trend indicator of the system’s performance parameters increase/decrease, even for the case of a “variable” manufacturing process, which changes dynamically.

4.1. Managerial Implications. The results obtained suggest that the \(\beta_{\text{MC4.0}}\) expression can be used as a trend indicator tool, but not as a predictor tool. It is our belief that the managerial implications of the \(\beta_{\text{MC4.0}}\) expression are promising, specifically in the area of production scheduling and programing of a manufacturing system operating within and Industry 4.0 context. As mentioned by [86], developing a production program/schedule is about to squeeze products through available resources, a very difficult task specially when dealing with a complex system—where this last fact is expressed in terms of options and constraints—and that often result on unfeasible or difficult-to-follow schedules [59]. Due to the flexibility exhibited by a manufacturing system operating within and Industry 4.0 context, the machine assignment and operation sequencing is known as flexible job shop scheduling, a very complex problem where traditional mathematic optimization methods are difficult to
| Scenario | $M_1$ | $M_2$ | $M_3$ | $M_{14}$ | $M_{23}$ | Total $\sum_t$ | $M_1$ | $M_2$ | $M_3$ | $M_{14}$ | $M_{23}$ |
|----------|-------|-------|-------|---------|---------|----------------|-------|-------|-------|---------|---------|
| 1        | 0     | 20.076| 0     | 33.924  | 2.076   | 15.924        | 72    | 27.883| 50    | 47.116  | 2.883   | 22.116 |
| 2        | 0     | 20.076| 41.004| 78.42   | 5.58    | 22.92         | 168   | 11.95 | 4.71  | 24.407  | 3.321   | 13.642 |
| 3        | 17.472| 32.424| 41.004| 95.424  | 19.092  | 34.572        | 239.988| 7.280 | 13.510| 17.085  | 39.761  | 7.955  | 14.405 |
| 4        | 34.308| 32.424| 78.408| 142.176 | 51.504  | 45.168        | 383.988| 8.934 | 8.444 | 20.419  | 37.026  | 13.412 | 11.762 |
| 5        | 56.916| 39.204| 89.892| 194.352 | 60.72   | 62.904        | 503.988| 11.293| 7.778 | 17.836  | 38.562  | 12.047 | 12.481 |
| 6        | 63.72 | 54.96 | 104.22| 236.976 | 107.292 | 80.82         | 647.988| 9.833 | 8.481 | 16.083  | 36.571  | 16.557 | 12.472 |
| 7        | 88.92 | 75.96 | 104.22| 287.376 | 139.692 | 95.82         | 791.988| 11.227| 9.591 | 13.159  | 36.285  | 17.638 | 12.098 |
| 8        | 119.232| 75.96 | 159.168| 369.792 | 170.952 | 112.872       | 1007.976| 11.828| 7.535 | 15.790  | 36.686  | 16.959 | 11.197 |
| 9        | 144.06| 82.164| 183.996| 426.072 | 221.844 | 141.84        | 1199.976| 12.005| 6.847 | 15.333  | 35.506  | 18.487 | 11.820 |
| 10       | 163.824| 113.928| 202.344| 489.6   | 270.552 | 151.728       | 1391.976| 11.769| 8.184 | 14.536  | 35.173  | 19.436 | 10.900 |

Table 13: Accumulated workload per manufacturing resource $M_r$. 

Total $\sum_t$ per $M_i$: 

- Scenario 1: 72
- Scenario 2: 168
- Scenario 3: 239.988
- Scenario 4: 383.988
- Scenario 5: 503.988
- Scenario 6: 647.988
- Scenario 7: 791.988
- Scenario 8: 1007.976
- Scenario 9: 1199.976
- Scenario 10: 1391.976
tackle within a reasonable amount of time [89]. By using the $\beta_{MC4.0}$ as a basis, a methodology to assess the degree of complexity of a production program/schedule could be developed and use it to find (or choose) more attractive and beneficial options.

5. Conclusions and Future Research

The international global dynamic competition impose a series of pressures due to the fact that customers tend to increase variant diversity, ask for smaller lot sizes, and demand shorter cycle times, while at the same time, to have the opportunity to design their own products/services without a high price premium. This concept of mass customization falls within the possibilities of an Industry 4.0 environment, where the level of manufacturing complexity increases with level of product customization. As currently there is no comprehensive metric that addresses the complexity derived from both the mass customization variety-induced complexity and from the adoption of the Industry 4.0 paradigm, in this research, it was proposed the first methodology to assess the degree of manufacturing resource behavior—is related to the level of workload of a manufacturing resource $M_i$, for each product, i.e.,

(1) Products 1 and 2 (Scenarios 1 and 2) do not use manufacturing resource $M_1$ (so, it appears as NA)
(2) Product 3 (Scenario 3) consumes two minutes
(3) Product 4 (Scenario 4) consumes two minutes and so on

(3) To introduce a complexity element derived from the information flow present in the product-to-product and machine-to-machine operation modes, as in this study it is assumed to be accurate, timely, consistent, and in the proper format, and that its handling is flawless

(4) To derive a correcting factor, so the proposed $\beta_{MC4.0}$ expression can be used a highly accurate predictor tool of the system’s performance parameters’ final values and not only as a trend indicator.

Appendix

In order to exemplify how the calculations presented in this document were performed, (1) the authors refer to Table 5 (probabilities $P_i$ for all the ten tested scenarios):

(i) Row “Processing time on $M_i$ (from Table 2)” shows the processing time consumed by manufacturing resource $M_i$, for each product, i.e.,

(1) Products 1 and 2 (Scenarios 1 and 2) do not use manufacturing resource $M_1$ (so, it appears as NA)
(2) Product 3 (Scenario 3) consumes two minutes
(3) Product 4 (Scenario 4) consumes two minutes and so on

(ii) Row “$\Sigma$ processing time” shows the accumulated time for each scenario, i.e.,

(1) As Products 1 and 2 do not use manufacturing resource $M_1$, the accumulated time is zero
(2) The accumulated time for Scenario 3 is two
(3) The accumulated time for Scenario 4 is two and so on

(iii) Rows $P_1$ through $P_{10}$, Scenario 10, shows the calculations for each product’s probability, i.e.,

(1) Scenario 1, $P_1 = NA/0 = NA$
(2) Scenario 2, $P_1 = NA/0 = NA$ and $P_2 = NA/0 = NA$
(3) Scenario 3, $P_1 = NA/2 = NA$, $P_2 = NA/2 = NA$, and $P_3 = 2/2 = 1$
(4) Scenario 4, $P_1 = NA/4 = NA$, $P_2 = NA/4 = NA$, $P_3 = 2/4 = 0.5$, and $P_4 = 2/4 = 0.5$ and so on

(2) The authors refer to Table 6 ($\beta_{MC4.0}$ values for manufacturing resource $M_1$):

(iv) Rows $P_1$ through $P_{10}$, Scenario 10, shows the calculations for each product’s $\beta_{MC4.0}$ values, using equation (3) (it must be noted that whenever a product $i$ processing time appears as NA, its associated $P_i$ is considered to be NA and its contribution to the $\beta_{MC4.0}$ expression value is considered to be zero), i.e.,

(1) Scenario 1, $\beta_{MC4.0} = (1/NA) \ast log(2/(1/NA)) = 0$
(2) Scenario 2, $P_1\beta_{MC4.0} = (1/NA) \ast log(2/(1/NA)) = 0$ and $P_2\beta_{MC4.0} = (1/NA) \ast log(2/(1/NA)) = 0$
(3) Scenario 3, $P_1\beta_{MC4.0} = (1/NA) \ast log(2/(1/NA)) = 0$, $P_2\beta_{MC4.0} = (1/NA) \ast log(2/(1/NA)) = 0$, and $P_3\beta_{MC4.0} = (1/1) \ast log(2/(1/1)) = 0$
(4) Scenario 4, $P_{4} \times MC4.0 = (1/NA) \times \log 2(1/NA) = 0$, $P_{5} \times MC4.0 = (1/NA) \times \log 2(1/NA) = 0$, $P_{6} \times MC4.0 = (1/0.5) \times \log 2(0.5/0.5) = 2$, and $P_{6} \times MC4.0 = (1/0.5) \times \log 2(1/0.5) = 2$, and so on.

(3) The authors refer to Table 9 (alternative manufacturing process routes, frequency, and processing time impact):

(v) For example, product 10 (2A3B1C), consumes two minutes of manufacturing resource $M_{1}$, three minutes of $M_{2}$, two minutes of $M_{3}$, and nine minutes of $M_{4}$:

1. $M_{1} \cdot M_{2} \cdot M_{3} \cdot M_{4}$ route is followed 47.1% of the time
2. $M_{1} \cdot M_{2} \cdot M_{3} \cdot M_{14}$, route followed 23.5% of the time
3. $M_{1} \cdot M_{2} \cdot M_{23} \cdot M_{4}$, route is followed 11.8% of the time
4. $M_{14} \cdot M_{2} \cdot M_{3}$, route is followed 5.9% of the time
5. $M_{14} \cdot M_{23}$, route is followed 11.8% of the time

(vi) The total consumed time by manufacturing resource is

1. $M_{1}$, is $2 \times (0.471 + 0.235 + 0.118) = 1.648$
2. $M_{2}$, is $3 \times (0.471 + 0.235 + 0.118 + 0.059) = 2.647$
3. $M_{3}$, is $3 \times (0.235 + 0.118 + 0.059) = 1.529$
4. $M_{4}$, is $9 \times (0.471 + 0.118) = 5.301$
5. $M_{14}$, is $9 \times (0.235 + 2 + 9) \times (0.059 + 0.118) = 4.051$
6. $M_{23}$, is $2 \times (0.118 + 2 + 3) \times (0.118) = 0.824$

(vii) The total combined time consumed by

1. $M_{1}$ and $M_{4}$ must be equal to $(2 + 9) = 11$ minutes, which is confirmed by adding 1.648 (from $M_{1}$) + 5.301 (from $M_{4}$) + 4.051 (from $M_{14}$)
2. The total combined time consumed by $M_{2}$ and $M_{3}$ must be equal to $(2 + 3) = 5$ minutes, which is confirmed by adding 2.647 (from $M_{2}$) + 1.529 (from $M_{3}$) + 0.824 (from $M_{23}$)

Data Availability

The DES model used to support the findings of this study is available from the corresponding author upon request.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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