# Internet of Things Technology Diffusion Forecasts

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***Abstract*—Prognosticators and pundits are forecasting an explosion over the next decade in the number of sensors connected to wired and wireless networks, also referred to as the Internet of Things. The challenge is that these sensor forecasts are being made without taking into account the infrastructure required to manufacture and operate the sensors. Financial forecasts of individual infrastructure components have been made, but they give point forecasts rather than diffusion curves. It is also often not clear what models these forecasters are using, as they are often in proprietary reports. The present study provides sensor and sensor infrastructure technology component diffusion forecasts using a sigmoidal model of product diffusion. A plurality of technology diffusion curves was computed, one for each sensor infrastructure component technology. To identify the potential lack of availability of a component or a set of components, the forecast curves were then examined for temporal commonalities and differences. Thus this study provides a method for forecasting an emerging technology.**

## I. Introduction

Prognosticators and pundits are forecasting an explosion over the next decade in the number of sensors connected to wired and wireless networks, also referred to as the Internet of Things [1, 2, 3, 4, 5, 6, 7, 8]. There were 12.5 billion of these so-called connected devices in 2010 [9]. The forecast numbers for 2020 range from 20 billion [4] to one trillion [10].

The challenge is that these sensor forecasts are apparently being made without taking into account the infrastructure required to manufacture and operate the sensors. A single so-called pre-forecast has been produced for sensor infrastructure diffusion [11] using the method of the technology landscape [12]. It is a pre-forecast because it identifies the components required of systems-level forecasts such as the heterogeneous integration technology roadmap [13], but it does not itself make a forecast. The landscape approach will be discussed below. It supports roadmapping efforts for emerging technologies.

Financial forecasts of individual infrastructure components have been made, but they give point forecasts rather than diffusion curves. For example, the global wireless sensor network market was forecast to reach $945 million by 2020 [14] and $1.8 billion by 2024 [15]. The global energy harvesting market was forecast to reach $974.4 million by 2022 [16]. The thermoelectric energy harvester market was forecast to exceed $1.1 billion by 2026 [17]. The 3D printing market was forecast by 2020 to reach between $7 billion and $21.3 billion [18]. It is also often not clear what models these forecasters are using, as they are often in proprietary reports. What is missing are forecasts using conventional sigmoidal models of both the sensors and the sensor infrastructure components.

The present study provides sensor and sensor infrastructure technology component diffusion forecasts using a sigmoidal model of product diffusion. A plurality of technology diffusion curves was computed, one for each infrastructure component technology. To identify the potential lack of availability of a component or a set of components, the forecast curves were then examined for temporal commonalities and differences. If commonalities among components in their asymptotic growth can be observed, then the future existence of a system becomes more plausible. If one or more components demonstrates scarcity while other components demonstrate diffusion, then there may be a problem in the availability of all of the components that are needed to construct the desired system.

The present study is relevant to those engaged in forecasting sensors and sensor infrastructure in particular and in forecasting disruptive technologies in general. It provides a traditional sigmoidal diffusion forecast. It also provides a method for using the conventional sigmoidal model to forecast an emerging technology.

## II. Theoretical Background

Forecasting and roadmapping efforts can provide practical information to each other. A diffusion forecast provides target dates to a roadmapping effort. The preliminary work for a third-generation technology roadmap identifies the technology components whose diffusion could be individually modelled with sigmoidal curves. The technique for forecasting the Internet of Things diffusion will now be discussed, followed by a discussion of how such technologies are roadmapped. This section ends with a discussion on forecasting the Internet of Things.

### *A. Sensor Growth Forecasts*

The forecast numbers of connected devices in 2020 range from 20 billion [4] to one trillion [10] (Table 1). These numbers can be approximately reproduced with linear and exponential models (Table 2; verified by the authors). Yet large-scale product diffusion traces a sigmoidal curve [19, 20, 21] not a linear or exponential curve. No justification for utilizing linear and exponential models has been offered. Neither is any justification likely plausible for large-scale diffusion (i.e., national or continental scale diffusion). The linear forecast has no basis in theory. The exponential forecast is based on supply side speculation (e.g., [1]), which on first principles cannot be a credible forecasting basis for demand side product adoption: the mere ability to produce a product in quantity (or the exponential increase in some performance parameter) does not guarantee a demand for that product. The large-scale diffusion of a disruptive technology will still trace out a sigmoidal curve, e.g., the diffusion of mobile telephony has been sigmoidal [22, 23]. This is true even if that technology offers a so-called exponential improvement in some performance parameter, because the sigmoidal curve describes the diffusion of a product through society and not the improvement over time of some performance parameter. Thus a sigmoidal model-based forecast of sensor diffusion is wanting.

TABLE 1.THE FORECAST NUMBERS OF CONNECTED DEVICES IN 2020.

| Source | Estimated Number of Connected Devices in 2020 (in billions) |
|---|---|
| [4] | 20.8 |
| [3] | 28.1 |
| [6] | 34.0 |
| [5] | 38.5 |
| [2] | 40.9 |
| [7] | 50.0 |
| [8] | 200.0 |
| [10] | 1,000.0 |

TABLE 2. NUMBER OF CONNECTED DEVICES, WITH DATA (YEARS 2003, 2010, 2015) AND FORECAST (YEAR 2020).

| Year | Connected Devices (billions) |
|---|---|
| 2003 | 0.5 |
| 2010 | 12.5 |
| 2015 | 25 |
| 2020 (forecast) | 39 (linear forecast)<br>851 (exponential forecast) |

It has been suggested that there were 500 million connected devices in 2003, 12.5 billion in 2010, and that there will be 25 billion in 2015 [9]. Forecasting models were derived from these three data points. The models follow. Linear: y=2.32*(year) - 4,646.68, p=0.15, $R^2$ = 0.94; Exponential: y=0.440587*(log(year)) - 883.25, p<0.005, $R^2$= 0.99

A basic decision must first be made: mechanistic or dynamic? Mechanistic sigmoidal modelling provides insight into how and why products diffuse. Dynamic sigmoidal modelling is based on the goal of computing the best model fit to the presented data points. The goal of the present study is the latter.

*B. Roadmapping Emerging Technologies*

Roadmaps were developed to address three questions: where are we, where do we want to go, and how do we get there [24, 25, 26]. The roadmap was initially developed in an era of simpler theory, when innovation models [27, 28] and roadmaps [26, 29] were linear. The first modern roadmap was introduced in 1945 [30], with widespread development in the 1970s led by Motorola and others [31, 32].

After the turn of the Millennium, second generation modifications to the technology roadmap concept were proposed for discontinuous innovations and disruptive technologies [33]. The technology roadmap concept was subsequently extended, in a third-generation version, to contemporary technologies that comprise multiple root technologies [12]. In particular, technology landscapes are focused on goals for technical performance parameters, or “critical dimensions,” that must be met by the component emerging technologies. Less complex technologies typically have a single critical dimension. For example, in the International Technology Roadmap for Semiconductors, process linewidth was the critical dimension [12]. The newer heterogeneous integration technology roadmap [13] also focuses on roadmapping systems integration rather than roadmapping individual technology components.

Emerging technologies are often really a suite of separate and independent component technologies that are still in the process of converging or fusing into a single technology-based product [12]. Each component technology has a critical dimension, such that the emerging technology is characterized by a suite of critical dimensions. These multiple critical dimensions may remain relevant even after the technologies have converged. For example, in a technology roadmap for wireless communication, multiple critical dimensions were used, including bandwidth, data capacity and spectral efficiency [34]. Emerging technologies often evoke social controversy, such that roadmaps are now considering non-technical environmental constraints, or “boundary conditions.” These are concerns and frameworks that comprise the socio-legal context in which the proposed emerging technological system will operate [12].

The technology landscape technique also differs from roadmaps in its treatment of Technology Readiness Levels (TRLs). Rather than assigning a single TRL to the emerging technology or even a single TRL to each of the component technologies, the new technique requires compiling the distribution of TRLs of each component technology [12]. This is a Herculean task for even a large organization.

There is an even more fundamental challenge when roadmapping an emergent technology. It arises from the fact that, as previously stated, these technologies often lack a unit cell, i.e., they themselves often comprise a plurality of independent technologies from diverse and non-overlapping sectors. Because these technologies are independent, their development is neither coordinated nor coordinatable. Even if a roadmap were produced, no one would follow it because at such an early stage in the technology convergence it exceeds the manufacturing scope of any single enterprise.

*C. Forecasting The Internet of Things*

The future IoT will be characterized by heterogeneous sensors that are printed, operate at low power, harvest energy from their environments, and transmit over wireless networks while protecting privacy and providing security [35, 36, 37, 38, 39, 40, 41]. Enabling technologies will comprise Radio Frequency Identification (RFID), Wireless Sensor Networks (WSN), and identification and/or addressing schemes [35, 36, 37, 41, 42]. The IoT will make use of energy harvesting and trade off performance to decrease energy usage [36, 41].

The Internet of Things is a convergent technology [43, 44], in contrast to a product surrounded by complementary products [45] or by an associated market infrastructure [46]. Technology convergence is the combination of multiple technological elements for creating new technological domains [44]. Fusion technologies in contrast merely fuse together products that traditionally stand alone in the marketplace [47]. The practical impact is that a convergent technology can be disruptive because, as a new technology, they can possess a new performance dimension [48].

## III. Methods

Product diffusion forecasts were performed with the Richards model [49]. The Richards model is a flexible, four-parameter model that is able to fit the full range of sigmoidal shapes. The Richards model was utilized because of its demonstrated ability to fit a sigmoidal curve to a low number of initial data points [19]. The Richards model is able to do this because it is a four-parameter dynamic model. The four parameters give it more versatility as compared to a three-parameter model. In addition, the dynamic, non-mechanistic nature frees the model from the assumptions of mechanistic models. The downside of using a dynamical model is that some insight into the underlying diffusion mechanism is lost. The present study is intended neither to replace nor to deny the value of mechanistic studies of Internet of Things diffusion.

The Richards model [49] was recently applied to technology diffusion data [19]. The model has been modified and reparameterized by several researchers. As modified by [50], the model is:

$$W_t = W^\infty[1-(1-m)\exp[-k(t-T^\infty)/m^{m/(1-m)}]]^{1/(1-m)}$$

where $W_t$ is the weight or growth at time t, $W^\infty$ is the asymptotic weight, k is the maximum relative growth rate per unit time, $T^\infty$ is the time to asymptote, and m is a shape parameter with the property that $m^{1/(1-m)}$ is the relative weight at time $T^\infty$

To identify the potential lack of availability of a component or a set of components, the forecast curves were then examined for temporal commonalities and differences. The time to asymptote $T^\infty$ was thought to be particularly relevant. If diffusions of components did not asymptote simultaneously, there could be shortages.

### *A. Data*

Data were found for three of the sensor technology infrastructure components: Total wireless sensor networks market global revenues [51, 52], Energy harvesting modules global revenues [53], and Number of 3D desktop printers sold globally [54]. Because these are new and emerging technologies, the scope of the data is not comprehensive. However, because it can be plausibly assumed that the diffusion will be sigmoidal, it is possible to compensate for the lack of scope of data by means of the ability to assume an s-shaped curve. The Richards model was utilized because of its demonstrated ability to fit a sigmoidal curve to a low number of initial data points [19].

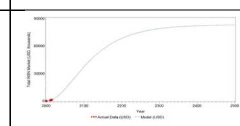
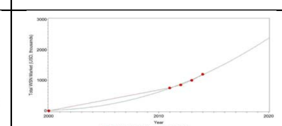
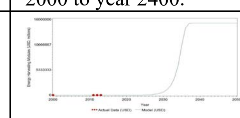
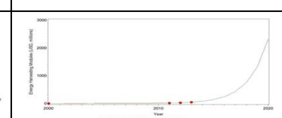
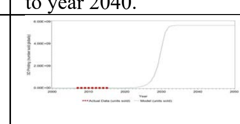
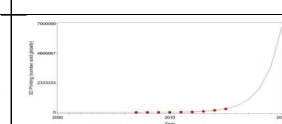
## IV. Results

Sigmoidal forecasts are provided below for the diffusion of wireless sensor networks, energy harvesting modules, and 3D printers (Table 3, Figs 1-3). To provide context, a fourth analysis was also performed on the sensor growth (Table 3, Fig 4). To identify the potential lack of availability of a component or a set of components, the forecast curves were then examined for temporal commonalities and differences. The years ($T^\infty$) of achieving asymptotic growth ($W^\infty$) of the three technologies are 2071 for wireless sensor networks, 2035 for energy harvesting modules and 2030 for 3D printing.

A forecast of sensor growth was computed. It has been suggested that there were 500 million connected devices in 2003, 12.5 billion in 2010, and that there will be 25 billion in 2015 [9]. The fit of the Richards model to the sensor data was statistically significant at Pr>F = 0.0174. The regression parameters were m=6.3983, $W^\infty$=550.90 (i.e., 550 billion sensors), $T^\infty$=2030 and k=0.1100 (Fig. 4). The number of sensors in 2020 is forecast at approximately 70 billion. In contrast to sensor forecasts of 20 billion to one trillion by 2020, the present study forecasts an asymptote of 550 billion sensors in 2030.

Table 3. Richards model parameters m, $W^\infty$, $T^\infty$, k, for the four data sets.

| **Technology** | **m** | **$W^\infty$** | **$T^\infty$** | **k** |
|---|---|---|---|---|
| Wireless sensor networks | 0.6092 | 83287.1 | 2071 | 0.00591 |
| Energy harvesting modules | 5.2942 | 15217550 | 2035 | 0.3100 |
| 3D printers | 3.9849 | 15217550 | 2030 | 0.3100 |
| Sensors | 6.3983 | 550.90 | 2030 | 0.1100 |

| **Techno-logy** | **Global data** | **Detail of global data** |
|---|---|---|
| Wireless sensor networks |  |  |
| | Figure 1a. Y-axis: global revenues (data: [79], [80]) X-axis: year 2000 to year 2400. | Figure 1b. Figure 1a in detail. X-axis: year 2000 to year 2020. |
| Energy harvesting |  |  |
| | Figure 2a. Y-axis: global revenues (data: [81]). X-axis: year 2000 to year 2040. | Figure 2b. Figure 2a in detail. X-axis: year 2000 to year 2020. |
| 3D desktop printers |  |  |
| | Figure 3a. Y-axis: number of 3D desktop printers sold globally (data: [82]). X-axis: year 2000 to year 2030 | Figure 3b. Figure 3a in detail. X-axis: year 2000 to year 2020. |

## V. Discussion

The combination of results suggests that the Internet of Things (IoT) will peak at 2030. These results also forecast that the asymptote of the wireless sensor network market will occur 40 years after the asymptotes of the energy harvesting module market, the 3D printing market and the sensor market. However, the concave up-concave down inflection points of the energy harvesting module market and 3D printing market occur immediately prior to achieving asymptotic growth, whereas the growth of the wireless sensor network market will be more gradual and continuous. Thus it may be the case that energy harvesting modules and 3D printing are limits to the growth of the sensor infrastructure until the third decade of the century. During the third decade, these two technologies will see rapid and effectively discontinuous growth, such that the growth in wireless sensor networks will then become limiting.

The parameter for achieving asymptotic growth in the wireless sensor market ($T^{\infty}$=2071) occurs well before the growth appears to asymptote (year 2300). Rather, the year appears to mark the inflection point in the curve from concave up to concave down (Fig. 1). In contrast, the years of achieving asymptotic growth for the other three curves does in fact match the year of achieving asymptote (Figs 2-4). The wireless sensor network analysis has comparatively smaller values of m and k. This suggests further study on the behavior of the reparameterized Richards model is warranted for such cases. As the Richards model is a graphical model rather than a mechanistic model, there may be no theoretical significance to these cases.

## VI. Conclusion

The sigmoidal diffusion curve was used to forecast independent technologies that are expected to converge to form the new sensor manufacturing and operating infrastructure. The results were statistically significant and mutually corroborative. They also set realistic limits for visions of a highly connected world with so-called ubiquitous sensing that are proposed by futurist social movements such as Abundance [1] and TSensors [10].

The primary limitation of this study was only four datasets were utilized. Future research could be directed towards constructing and analyzing a more comprehensive group of datasets. The method could also be tested against data from past emerging technologies. Another limitation is that the Richards model is a dynamical rather than a mechanistic model. The present study is intended neither to replace nor to deny the value of mechanistic studies of Internet of Things diffusion. A comparison of the results of the regressions in the present study, with regressions on the same data by mechanistic models such as Bass, Gompertz and Logistic, would be of interest but is beyond the scope of the research question of the present study.

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