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Random Walk Forecast of Urban Water in Iran Under Uncertainty[1]

Iman Ferdosian and Naim Haie

Civil Engineering Department, University of Minho, 4800-058 Guimarães, Portugal

E-mail: Iman_fn2007@yahoo.com, naim@civil.uminho.pt

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Abstract—There are two significant reasons for the uncertainties of water demand. On one hand, an evolving technological world is plagued with accelerated change in lifestyles and consumption patterns; and on the other hand, intensifying climate change. Therefore, with an uncertain future, what enables policy-makers to define the state of water resources, which are affected by withdrawals and demands? Through a case study based on thirteen years of observation data in the Zayandeh Rud River basin in Isfahan province located in Iran, this paper forecasts a wide range of urban water demand possibilities in order to create a portfolio of plans which could be utilized by different water managers. A comparison and contrast of two existing methods are discussed, demonstrating the Random Walk Methodology, which will be referred to as the "On-uncertainty path", because it takes the uncertainties into account and can be recommended to managers. This On-Uncertainty Path is composed of both dynamic forecasting method and system simulation. The outcomes show the advantage of such methods particularly for places that climate change will aggravate their water scarcity, such as Iran.

Keywords: uncertainty, dynamic forecasting, Isfahan, Random Walk, water resources, Iran

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INTRODUCTION

Water planning is impacted by greenhouse warming, which includes a wide spectrum of uncertain variations, encompassing: fluctuations in runoff, precipitation, temperature patterns, changes in demands, and water supply [4]. Other significant variables that influence water planning include: the wide changes in population growth, socio-economic evolution, globalization and other unforeseen phenomena [7]. One step to assist policy makers in water resources management to find an optimal allocation for different sections, undoubtedly, is predicting a future demand. There are important, yet changing, parameters which make it difficult to calculate the optimal demand. These parameters include: population, climate change, impossibility for data acquisition, and other forecasting drivers, particularly in arid and semi-arid areas. This scenario has made it problematic for futurists to be neither utopian nor idealistic [15]. As Madani and Mariño [13] discussed, the correlation between the aforementioned drivers of uncertainty to make an integrated study in a catchment is actually an exacerbating matter. It has been observed that economic development increases the resident's utility, which in turn is followed by population growth, an increase in water consumption and demand, and consequently, leads to increases in resident's utility. This cycle continues as a loop of a socio-economic and political subsystem. In this regard, the trend-breakers are referred to as specific uncertainty drivers, such as economic crisis, political shifts, new technologies and discoveries, and new market conditions. These events have all contributed to major disruptions to stability throughout the globe in the recent past [12]. Consequently, a significant step towards a sustainable development model is to increase the public's awareness and ability to manage climate risk and uncertainty, which will decrease the vulnerability of stakeholders, particularly households [9]. Meanwhile, other theories to control the uncertain future have been implemented through a focus on increasing efficiency in order to reduce water demand and consumption with a goal of sustainability [6, 8].

The main objective of the presented study is to compare and contrast two different methods to predict the future water demand in Isfahan province, located in Zayandeh Rud River basin in Iran, by simulating thirteen years from 1999 to 2011 and predict the water demand for 2030 by considering the On-uncertainty Method.

CASE STUDY AND CHARACTERISTICS

The reason why this basin was chosen is that approximately 90% of Iran is arid or semi-aired [2]. Moreover, as depicted in Table 1, Iran has been ranked the fifth country in the top 10 groundwater-abstracting countries in the world, from which approximately 72%

[1] The article is published in the original.

of the groundwater abstraction takes place globally [22] and Zayandeh Rud, with a length of 450 km, is situated in the Markazi basin as one of the most operational basins in the central part of the country.

Therefore, it plays an undeniable role in water supply to various stockholders as the major water resource in Isfahan (Fig. 1). It is essential for any organization and policy makers to understand the future demand, cope with the amount of supply, and adapt the water releases and withdrawals in order to balance the water in this basin.

The quantities for urban water demand, depicted in Table 2, consist of household, communal, public, commercial, industrial and green area in Isfahan province.

Table 1. Top 10 countries in annual abstracted water [22]

Country	Abstraction, km^3/year
1. India	251
2. China	112
3. United States of America	112
4. Pakistan	64
5. Iran	60
6. Bangladesh	35
7. Mexico	29
8. Saudi Arabia	23
9. Indonesia	14
10. Italy	14

METHODOLOGY

Point Projection

A widely used method by statisticians based on historical data is point procedure or off-uncertainty path (OFUP). In this method a time series based on historical data is needed based on which a trend that is a polynomial function of time would be drawn as a regression line (Fig. 2) to predict unforeseen future (e.g., [10, 14]). In some literatures “non-stationary” refers to time series and the term “deterministic” to any trend. Therefore, generally this method is considered as a non-stationary and deterministic [11]. The inherent characteristic of any trend, even with a perfect goodness of fit, is that it overlooks the uncertainty. Besides, high sensitivity of OFUP to the selected time interval is a matter of concern. However, in recent years some methods have been excogitated and added to theses common ones to mitigate the innate uncertainty in the systems [1], more experience is needed.

As can be seen in Figs. 2 and 3 the projected urban water demand for 2030 is around 575 million m^3 (MCM) with the historical data from 1999 to 2011 while, by limiting the time interval to 2008–2011 the forecast for 2030 will be decreased to 400 MCM which is approximately 70% of the former. Likewise, the anticipated demand for 2030 with the trend composed of 2001–2003 time intervals will touch an irrational point.

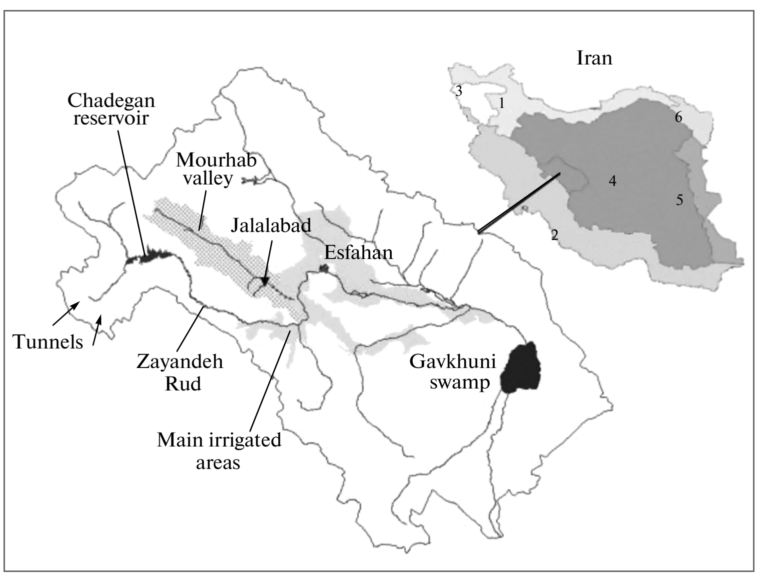

Fig. 1. Zayandeh Rud basins in Iran [2, 16].

Table 2. Urban water demand in Isfahan Province [20]

Year	Urban Water demand, 1000 m^3
1999	176512
2000	175900
2001	223257
2002	195579
2003	208923
2004	240239
2005	245633
2006	261589
2007	263249
2008	302901
2009	310639
2010	323379
2011	312773

Accordingly, due to these faults and also inaccessibility to unforeseen future, forecasting based on single-number or "point" projections would be unrealistic. These methods, even with considering confidence intervals as shown in the following parts, do not take into account the proper uncertainties in forecasting. Furthermore, trends have some crucial problems. They are based on this assumption that the probability or the shape of the future events personates those that formed the past and they are always based on deficient data. So, finding a useful method to point out the extreme uncertainties around the forecasts, those could be effective in decision making process of any system design, seems to be inevitable instead of point projections [17]. In this regard, some authors reminisce that water sector cannot be excellently gratified, exposing future extremes of climate change, only based on prevalent methods [5].

Dynamic Forecasting

To address uncertainty, different dynamic forecasting methods have been used through them the Random Walk has shown its aptitude to embrace the uncertain future while, looking back step by step to the past events.

This method is one of the on-uncertainty paths (OUP) in which, some researchers are fascinated to see what will happen in a distant future according to past records. As Neufville and Scholtes [17] explicate, through Random Walk a trend will be defined and a random error will be added to this trend based on the distribution of differences between the regression line or trend line and the real past data to add uncertainty to the trend. Therefore, through a Monte Carlo simulation, infinite random errors could be generated to shape future scenarios and amongst them a limited number of paths will be selected by decision makers. According to different polynomial equation for trend lines, random walk has been divided to:

1-simple random walk

$$X(t) = X(t-1) + \varepsilon(t). \qquad (1)$$

As can be clearly seen, the errors can be obtained only by subtracting the consecutive numbers and then based on their distribution function, the future could be simulated.

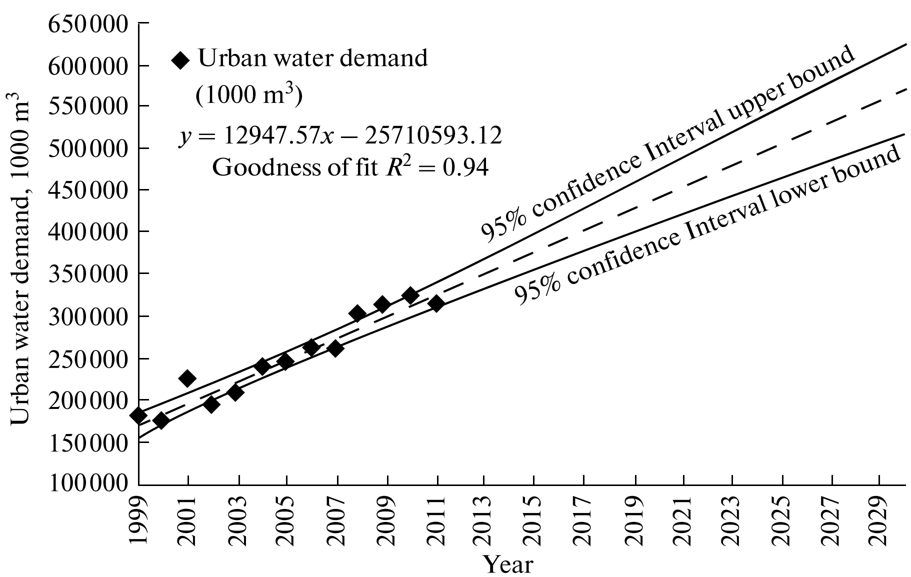

Fig. 2. OFUP for 2030 according to 1999–2011 historical data with its 95% CI.

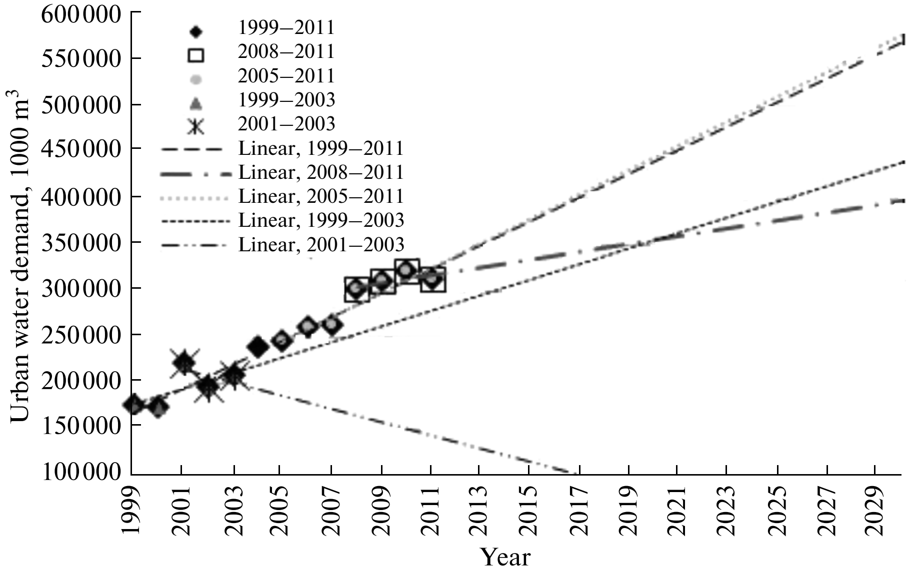

Fig. 3. OFUP for 2030 according to historical data in different interval times.

2-Additive model

$$X(t) = aX(\dot{t} - 1) + b + \varepsilon(t), \quad a \neq 1,\ b \neq 0 \qquad (2)$$

a and b are the appreciation or depreciation nonrandom factor and the intercept of the trend respectively, obtained from Fig. 4 with the random error $\varepsilon(t)$ around this trend based on normal distribution of historical data, that could be both negative and positive.

3-Multiplicative model

$$X(t) = \exp(b + \varepsilon(t))X(t-1)^a, \quad X(t) > 0 \ \text{for all}\ t \geq 0. \qquad (3)$$

This general equation can turn into an additive model by a log-transformation as shown in Eq. (4):

$$z(t) = az(\dot{t} - 1) + b + \varepsilon(t), \qquad (4)$$

where $z(t) = \log X(t)$, $X(t) > 0$ for all $t \geq 0$, $\varepsilon(t)$ are errors as defined for Eq. (2), a and b are numerical coefficients obtained by the regression procedure from Eq. (4) as depicted in Fig. 5.

RESULTS

In our case study, as illustrated in Fig. 4, the appreciation fix factor for the additive model trend is equal to 0.89. Besides, the distribution of errors has a mean of 6.25 and standard deviation of 20167.8.

For the multiplicative model in Fig. 5, the fix factor is equal to 0.849 with a mean and standard deviation for distribution of errors equal to 0.00023 and 0.0891, respectively. The goodness of fit for both models is almost the same in this special case study and its related data during 1999–2011.

According to these functions and the distribution functions of these errors, different scenarios have been

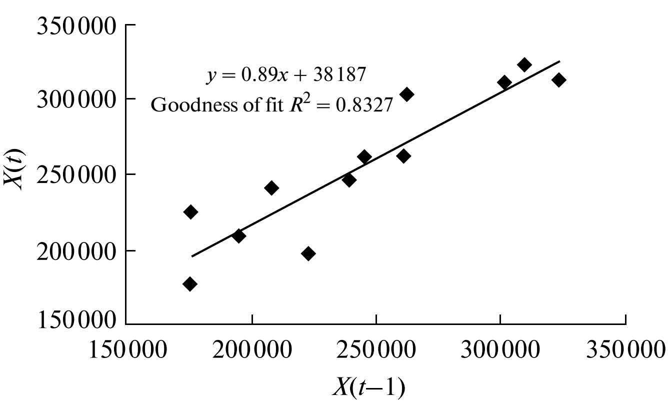

Fig. 4. Regression model for Eq. (2) [$X(t) = aX(t-1) + b + \varepsilon(t)$].

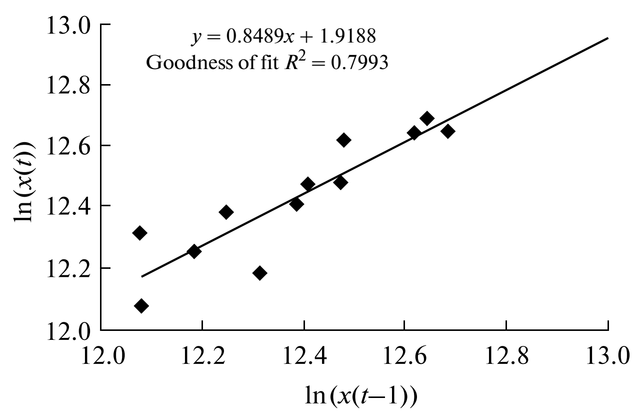

Fig. 5. Regression model for Eq. (4) [$\log X(t) = a\log(X(t-1) + b + \varepsilon(t)$].

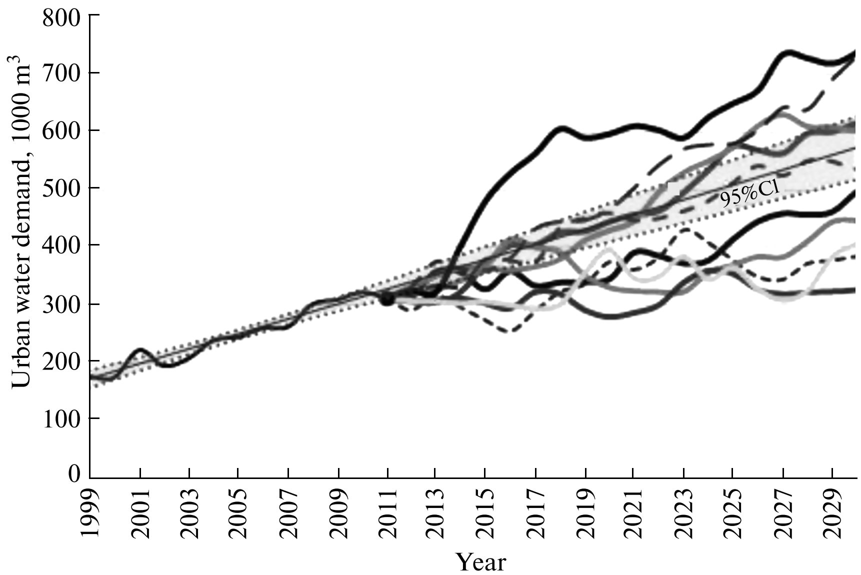

Fig. 6. Ten paths based on Simple random walk (Eq. (1)) compared with OFUP and its 95% CI.

simulated by Monte Carlo simulation in Microsoft Excel to forecast the urban water demand in Zayandeh Rud River basin in Isfahan province.

DISCUSSION

It is evident in Fig. 6 that, over a long time horizon the random walk is blowing up. Accordingly manager should be prepared to cope with a demand between a minimum around 255 MCM to a maximum almost 739 MCM for 2016 and 2030, respectively. The reason why the lower point of these predictions would be even lower than the water demand in 2011 could be related to new high-tech lifestyles, birth control policies or even dietary changes in all of which, the water consumption has been controlled. On the other hand, the upper point in these varieties, which are much greater than the corresponding demand on the trend line, could be a consequence of the ungovernable population or other drivers of uncertainty. Due to this unpleasant fact, one can claim that the common trend is much more realistic since designing any system based on this funnel seems to be a robust decision-making, under which all extreme events could be bridled and accordingly it would burden any cost-efficient decision making [18]. Besides, this funnel would throw one in the swamp of “the flaw of average” [19]. By the same token, however the prevalent trend line is in the middle of the fluctuating funnel as an average line or expected value of all the paths, it overlooks the variations which has undeniable effects on any decision making process. The question is which demand finally should be considered for any system design in 2030?

To respond to this question, Fig. 7 clarifies different paths based on additive random walk in which the paths fluctuate mildly around the demand in 2011. However this method embraces more uncertainty, it ignores the extreme uncertain demands in coming years. As depicted in Fig. 7, the policy makers should be equipped for a variation between 222 to 483 MCM for the whole time interval between 2011 and 2030. The point is that these maximum and minimum points happen for the first time in 2021 and not before that which should be of great attention from the view point of decision makers.

Moreover, to address the aforementioned question another method has been applied in which ten paths based on multiplicative random walk has been drawn. As depicted in Fig. 8, this later method has the advantages of the former ones. In other words, despite of the fact that it includes the wide uncertainty and randomness in its shape, it has a rational increase over time looking down to the probability of decreasing the water demand. As one can observe, the minimum demand during these 19 years of simulation is almost 209 MCM while, the maximum forecasted demands for 2020 and 2030 are around 506 and 527 MCM respectively while the maximum demand in the whole period would be 559 MCM in 2017.

By comparing the three methods, one can come to the understanding that although the minimum foreseen for the future would be around 220 MCM, the maximums alter wildly from 739, 483 and 559 MCM for simple, additive and multiplicative random walk respectively. It is of interest to note that using 95% C.I., the 2030 maximum and minimum demand values are 628 and 518 MCM respectively which do not cover the maximum and minimum values obtained from aforementioned methods.

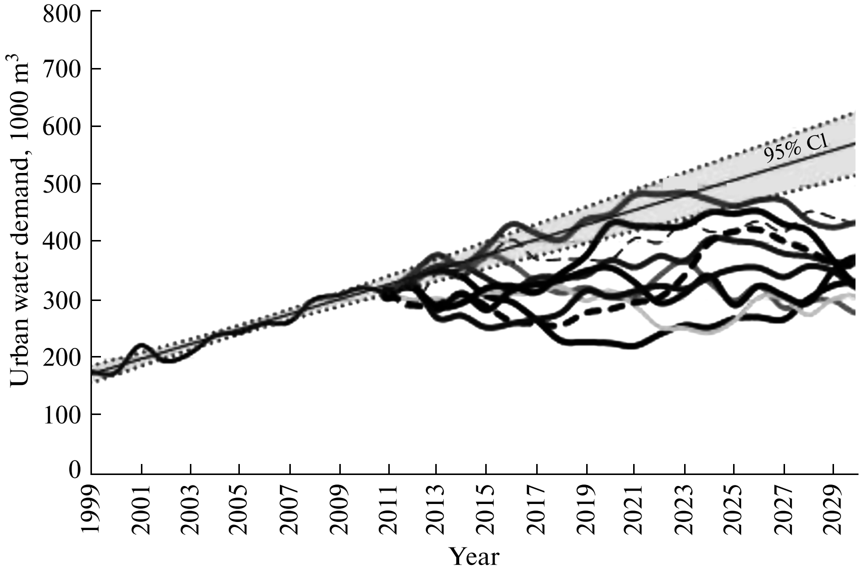

Fig. 7. Ten paths based on Additive random walk (Eq. (2)) compared with OFUP and its 95% CI.

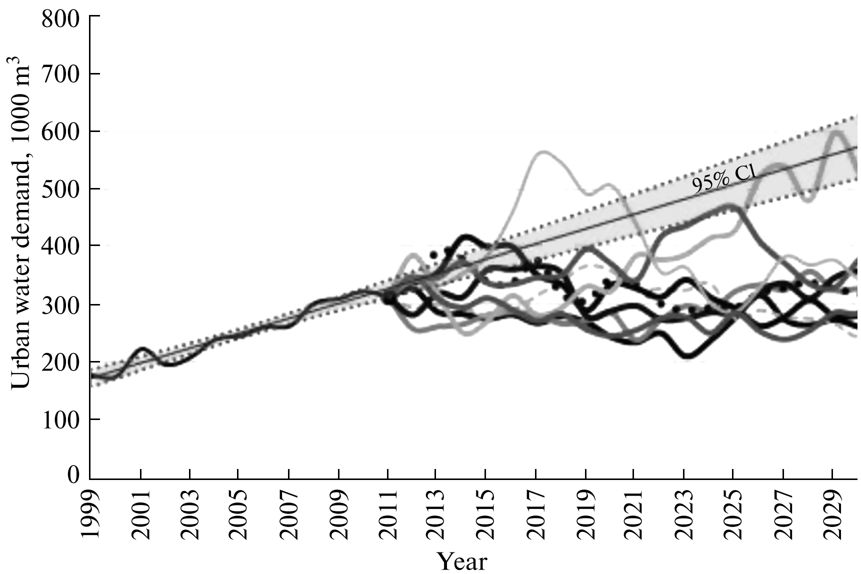

Fig. 8. Ten paths based on Multiplicative random walk (Eq. (3)) compared with OFUP and its 95% CI.

Finally, to predict the future demand a point projection could be selected, but various paths should be a matter of concern for responsible decision makers who want to design their systems in response to uncertainties. In addition, selection amongst the future scenarios is a dance of scientific reasoning and political preferences [12]. In other words, although analysis as reasoning is definitely essential in decision-making process, considering emotional and political preferences would be also a reality which should be taken into account for an efficient navigation in this multifaceted and ambiguous world [3, 21].

CONCLUSIONS

In this paper we forecasted a wide range of urban water demand possibilities according to future uncertainty in Isfahan province located in Zayzndeh Rud River basin in Iran by simulating future 19 years through 13 observed years based on which a portfolio of plans would be achieved by different water managers. Anticipation has been done through two existing methods, the primitive one is based on a prevalent so-called point projection method, "Off-uncertainty path" by which we obtained a demand around 550 MCM for 2030 while, the subsequent new methodology, "On-uncertainty path," which takes into account the uncertainties and recommended to managers, works based on a random walk which is a dynamic forecasting method by system simulation and concluded a wide range of possible future with a wild fluctuation and uncertainty embracement. All these OUPs propose a maximum demand equal to 739 MCM in 2030 and a minimum demand equal to 209 MCM in 2023 which all should be taken into account in decision making process. Despite of the fact that, the point prediction method brings any decision maker to feel being at home, it overlooks the probability of any variations and blindfolds the managers to the uncertain future even with considering 95% confidence interval. Consequently, the Random Walk, particularly multiplicative one, works better under different circumstances and has the opportunity to utilize decision maker's affection and reasoning being able to adapt their systems or designs better for a future with countless uncertainties.

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