

CHAPTER 6

CHAOS THEORY BASED MODELS OF SIMPLE SYSTEMS OF CONGESTION

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6.1 Introduction

When embarking on the use of Chaos Theory in modelling simple Systems of Congestion it is considered prudent to provide a benchmark based on the **classical M/M/1 queue** to serve as the necessary introductory backdrop to the investigation:

6.1.1 The classical Poisson arrival system

6.1.1.1 The general modelling approach

Modelling a completely random arrival process traditionally involves using the Poisson distribution (negative exponentially distributed inter-arrival times) as the cornerstone of analysis in generating an ordered sequence of arrival events. This implies that the arrival system is treated as being Markovian.

If arrivals are considered to occur within a temporal sequence of equal time intervals, the cumulative Poisson distribution can adequately generate arrivals with the passage of time.

The Poisson distribution of arrivals is given by

$$P_n = \frac{\lambda^n e^{-\lambda}}{n!} \quad n=0,1,2,\dots \quad \text{and } \lambda > 0 \quad (6.1)$$

where n = no. of arrivals in a given time interval

λ = average no. of arrivals in the temporal sequence of time intervals

An example of the generation of a Poisson based arrival process for $\lambda = 8$ over 200 one minute time intervals is shown in Fig. 6.1.1.

The generation of the arrival process is driven by a random number generator. The adequacy of the generation process is demonstrated by the achieved results.

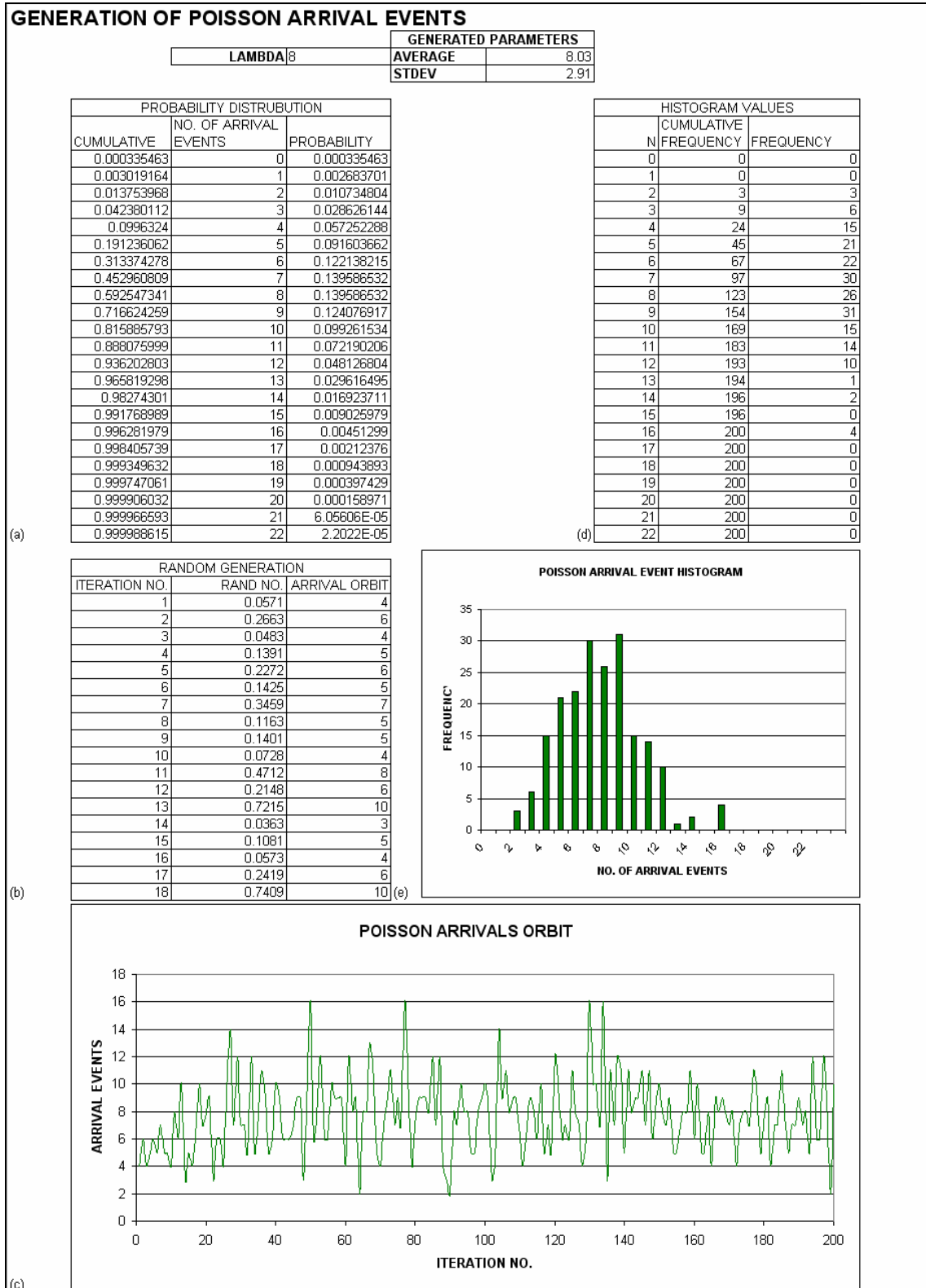


Fig. 6.1.1 GENERATION OF THE ORBIT OF POISSON ARRIVAL EVENTS

6.1.2 The classical exponential service system

6.1.2.1 The general modelling approach

In a similar fashion to the modelling of completely random arrivals (See par. 6.1.1), the modelling of a single completely random service process often involves the Poisson distribution (negative exponentially distributed service times) in generating an ordered sequence of service events. This implies that the service system is treated as being Markovian.

If consecutive service events are considered to occur within a temporal sequence of equal time intervals (synchronously identical to the arrival time intervals) the cumulative Poisson distribution can adequately generate service events with the passage of time.

The Poisson distribution of service events is given by

$$P_n = \frac{\mu^n e^{-\mu}}{n!} \quad n=0,1,2,\dots \text{ and } \mu > 0 \quad (6.2)$$

where n = no. of service events **offered** in a given time interval
 μ = average no. of service events **offered** in the temporal sequence of time intervals

An example of the generation of the service process for $\mu = 10$ over 200 one minute time intervals is shown in Fig. 6.1.2

The generation of the service process is driven by a random number generator. The adequacy of the generation process is demonstrated by the achieved results.

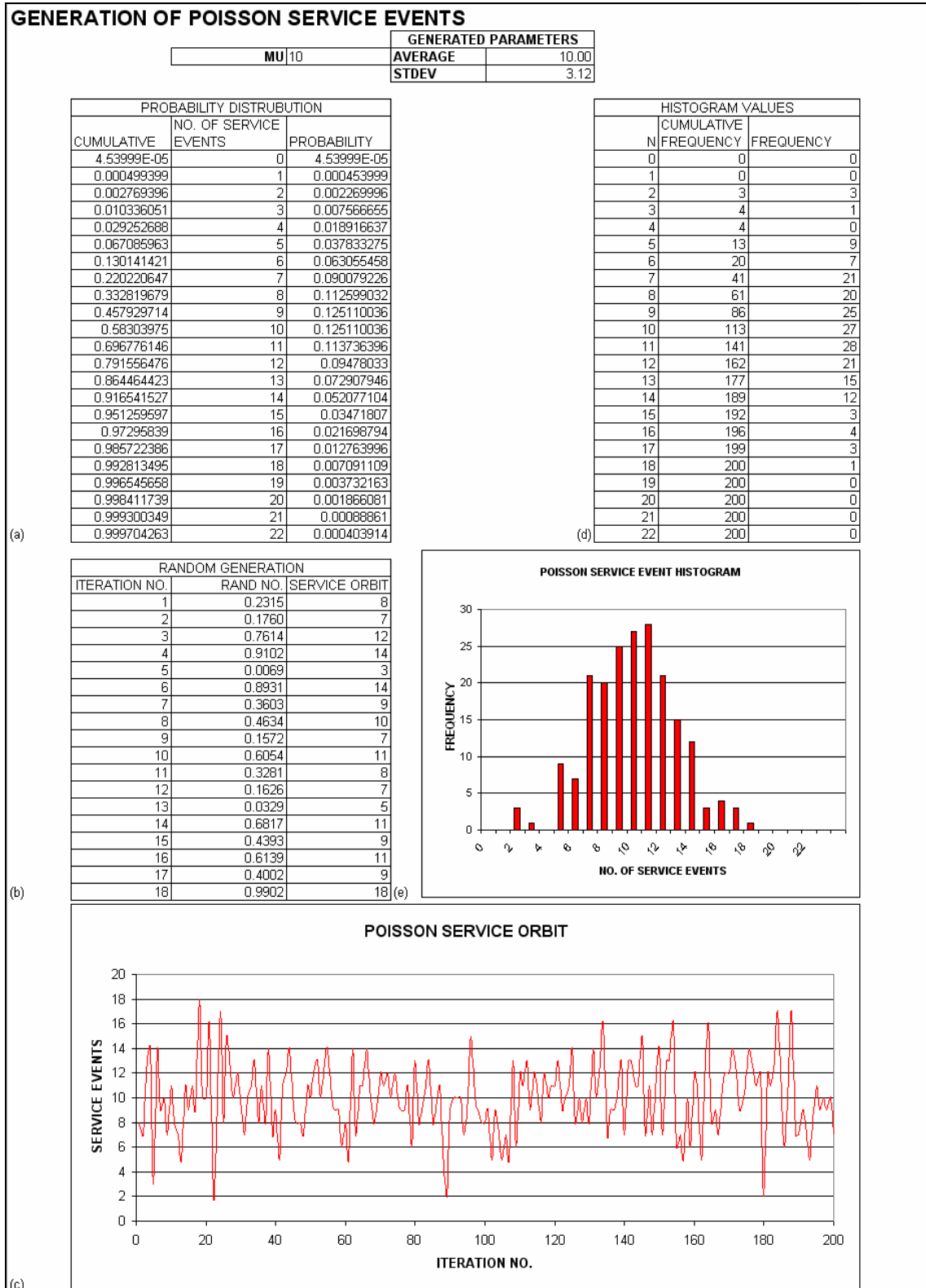


Fig. 6.1.2 GENERATION OF THE ORBIT OF POISSON SERVICE EVENTS

6.1.3 The classical M/M/1 queue

6.1.3.1 The general modelling approach

From the point of view of analyzing Systems of Congestion recent significant developments have addressed approximations and numerical techniques in manipulating steady-state and non steady-state systems. With this in mind and obeying the requirement of **model simplicity and robustness**, the concept of studying ***a temporal sequence of equal time intervals*** plays a central role in modelling the M/M/1 queueing system as it deals with arrival and service events. The novelty of the proposed system model is based on the flow of entities as follows: During a given time interval (t) the number of entities in the system at the end of time t equals the number of system entities at the beginning of time t plus the number of arrival events in time t minus the number of service events offered (available) in time t , i.e.

$$\begin{aligned} \text{No. in system at the end of } (t + \Delta t) = & \quad [\text{No. in system at the beginning of } t] + \\ & \quad [\text{No. of arrival events in } \Delta t] - \\ & \quad [\text{No. of service events offered in } \Delta t] \quad (6.3) \end{aligned}$$

The model calculates the average number in the system during the interval (Δt) as follows:

If the number of service events offered in Δt exceeds the sum of the number in the system at t plus the number of arrival events in Δt , the average number of units in the system during Δt is given by:

$$\begin{aligned} & \quad [(\text{No. at } t + \text{No. of arrival events in } \Delta t) / 2] \times \\ & \quad [(\text{No. at } t + \text{No. of arrival events in } \Delta t) / \\ & \quad (\text{No. of service events in } \Delta t)] \quad (6.4) \end{aligned}$$

If the sum of the number in the system at t plus the number of arrival events in Δt exceeds the number of service events offered in Δt the average number of units in the system during Δt is given by:

$$\frac{[(\text{No. at } t + \text{No. of arrival events in } \Delta t) + (\text{No. at } t + \text{No. of arrival events in } \Delta t - \text{No. of service events offered in } \Delta t)]}{2} \quad (6.5)$$

A model of the events which take place within a time interval is an example of a highly simplified model of a deterministic **instantaneous** replenishment inventory system which allows shortages to occur during the time interval i.e. when some service events are analogously on offer but not used within the interval as a result of insufficient arrivals.

One may speculate that such an elementary model does not meet the requirement of mathematical elegance, or that an attempt is being made to approach the modelling problem pragmatically to avoid immersion into higher mathematics. At this juncture of the modelling process one should await the results which follow, results which are based on further development of the system modelling approach before prematurely judging the merit of the model.

The resulting orbit of number of entities in the system which is obtained by merging the arrival and service processes used in sections 6.1.1 and 6.1.2 does not deliver the required theoretical mean number in the system for the temporal sequence of time intervals. To compensate for this state of affairs the data stream of system entities must be manipulated by means of a **designer equation**(Appendix B) The designer equation is a necessary adjunct to equations (6.3) and (6.4) to shape the data stream of system entities to reflect reality of system operation modelled via passing reference to interevent times (arrival and service).

The generation of the system state with the passage of time is driven by random number generation and is shown in Fig. 6.1.3. The adequacy of the generation process, which includes the use of a designer equation, is demonstrated by achieved results.

The model can now be used in spreadsheet form for the analysis of steady state and transient operation of an M/M/1 queue. Consequently it may also serve as a ***touchstone*** in evaluating the use of the Chaos based models which follow. One should however not lose sight of the fact that the Poisson/exponential assumption is a mathematical concept and that no real process can be expected to constantly be in agreement with it. It is however heartening to know that use of it as a benchmark will lead to a conservative evaluation of alternative modelling methods.

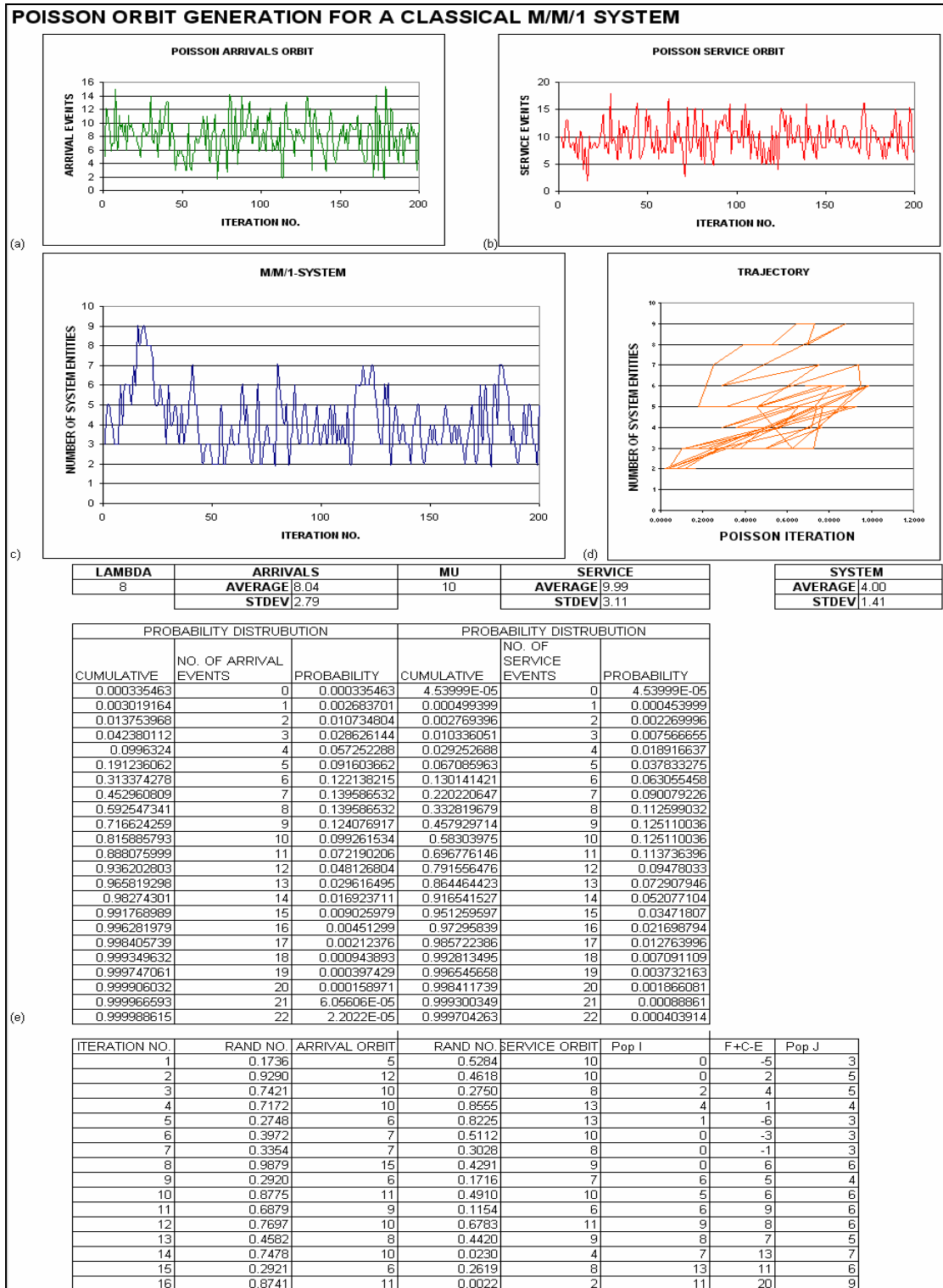


Fig. 6.1.3 GENERATION OF THE ORBIT OF A CLASSICAL POISSON M/M/1 SYSTEM

6.2 Introduction to Chaos generation

Having established the classical M/M/1 queue as the benchmark for the general use of chaos based models the research may progress to create the relevant method of analysis for a chaos driven single channel queue with an average arrival rate of $\lambda=8$ and an average service rate of $\mu=10$. The initial research efforts are based on:

- Verhulst logistic mapping
- Weibull based mapping
- Trigonometric mapping

Fig. 1.1 serves as an example which displays the nature of iterative mapping of the Verhulst type.

6.2.1 The Verhulst generated arrival system

6.2.1.1 The general modelling approach

In attempting to emulate arrival events of an M/M/1 system by using the Verhulst logistic generation method it is necessary to at least achieve “Poissonness” (Grosh [4]) by:

- selecting an appropriate logistic parameter to ensure that “chaotic” randomness is generated, and
- creating an emulated mean and standard deviation which are related as in a Poisson distribution.

At this juncture it must be emphasized that the use of a designer equation (Appendix A) becomes mandatory to fashion the data stream of generated arrivals effectively.

An example of the temporal sequence of the number of arrival events in equal time intervals for an average arrival rate of $\lambda=8$ as generated by a Verhulst logistic model over 200 one minute time intervals is shown in Fig. 6.2.1. The adequacy of the generation process is demonstrated by the achieved results.

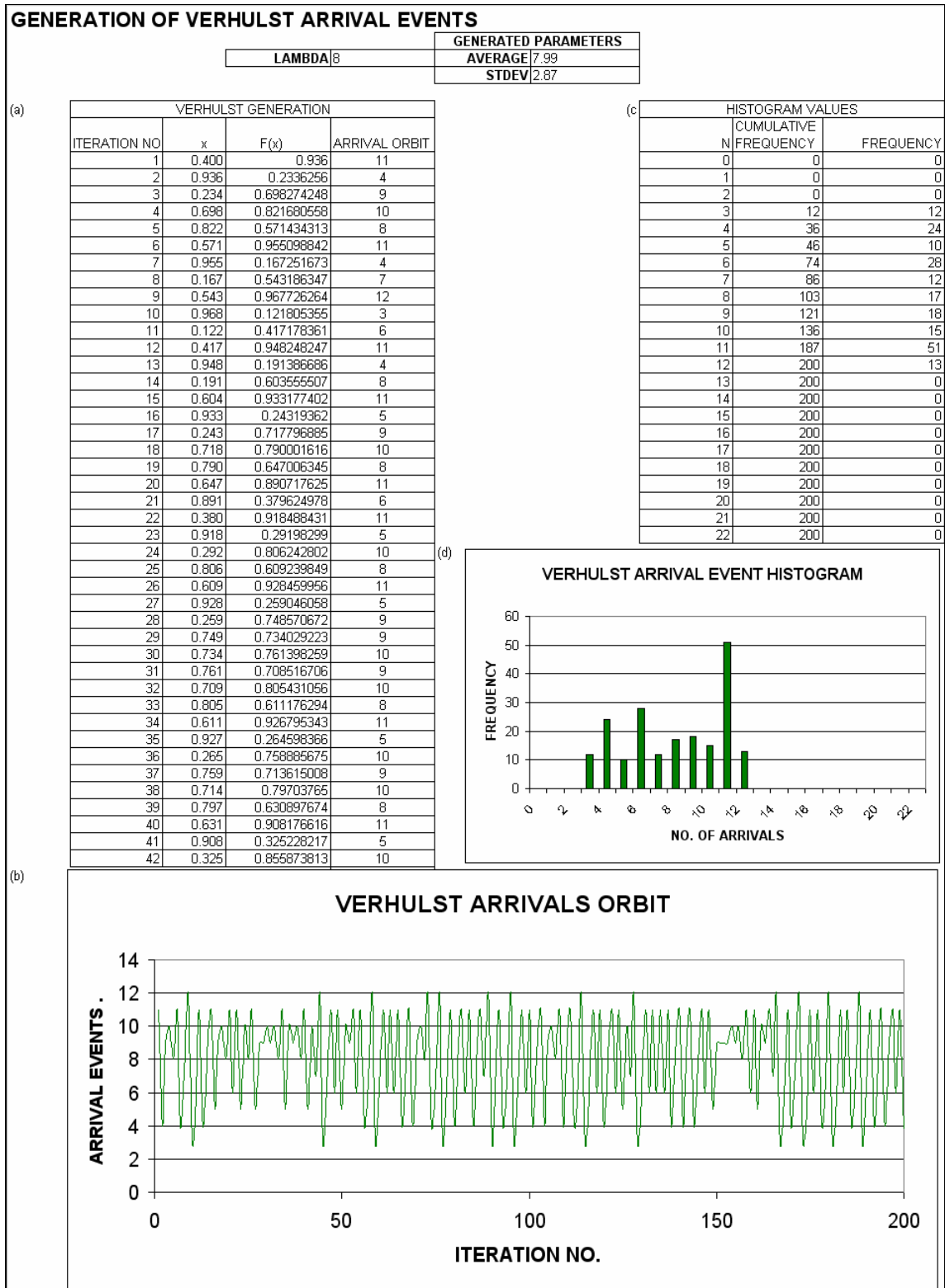


Fig. 6.2.1 GENERATION OF THE ORBIT OF VERHULST ARRIVAL EVENTS

6.2. The Verhulst generated service system

6.2.2.1 The general modelling approach

In attempting to emulate service events of an M/M/1 system by using the Verhulst generation method it is necessary as in the case of arrival events to at least achieve “Poissonness” (Grosh [4]) by:

- selecting an appropriate logistic parameter to ensure that “chaotic” randomness is generated, and
- creating an emulated mean and standard deviation which are related as in a Poisson distribution.

An example of the temporal sequence of the number of service events in 200 one minute equal time intervals for an average service rate of $\mu=10$ as generated by a Verhulst logistic model is shown in Fig. 6.2.2. The adequacy of the generation process is demonstrated by the achieved results.

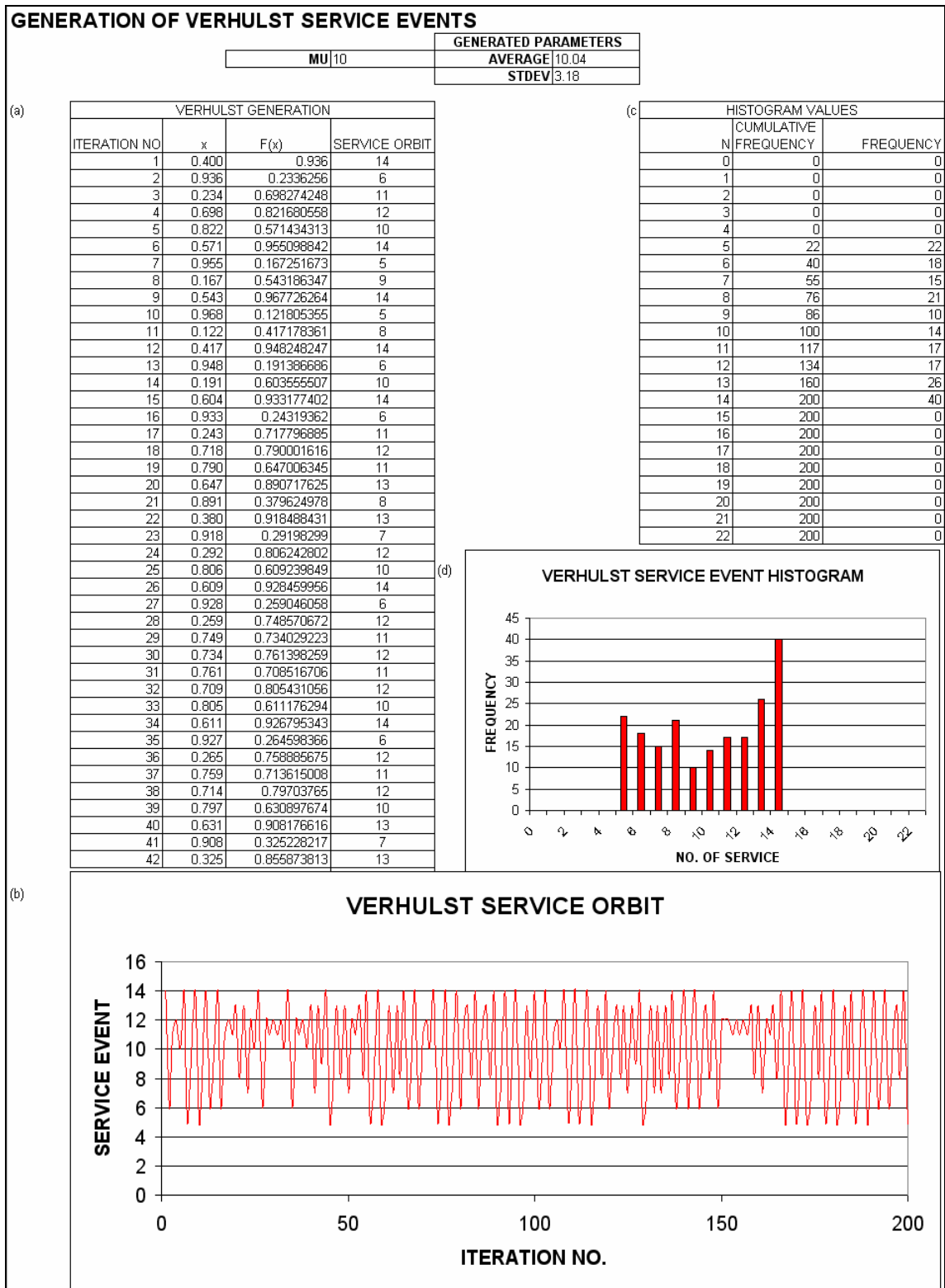


Fig. 6.2.2 GENERATION OF THE ORBIT OF VERHULST SERVICE EVENTS

6.2.3 The Verhulst generated single channel queue

6.2.3.1 The general modelling approach

If as at the outset of this chapter considering the use of chaos generation methods to model a single channel queueing system by means of approximations and numerical techniques is heeded, and robustness and simplicity of modelling is to be achieved, the concept of studying a temporal sequence of equal time intervals which accommodate arrival and service events is justified.

As in the case of the classical M/M/1 queue analysis of par. 6.1.3.1 the Verhulst system model makes use of the highly simplified model described in equation (6.3) which also requires manipulation of the generated data stream by ***designer equations***.

The generation of the system state with the passage of time is driven by chaos iterative generation and is shown in Fig 6.2.3. The adequacy of the generation process, which includes the use of a designer equation, is demonstrated by the achieved results.

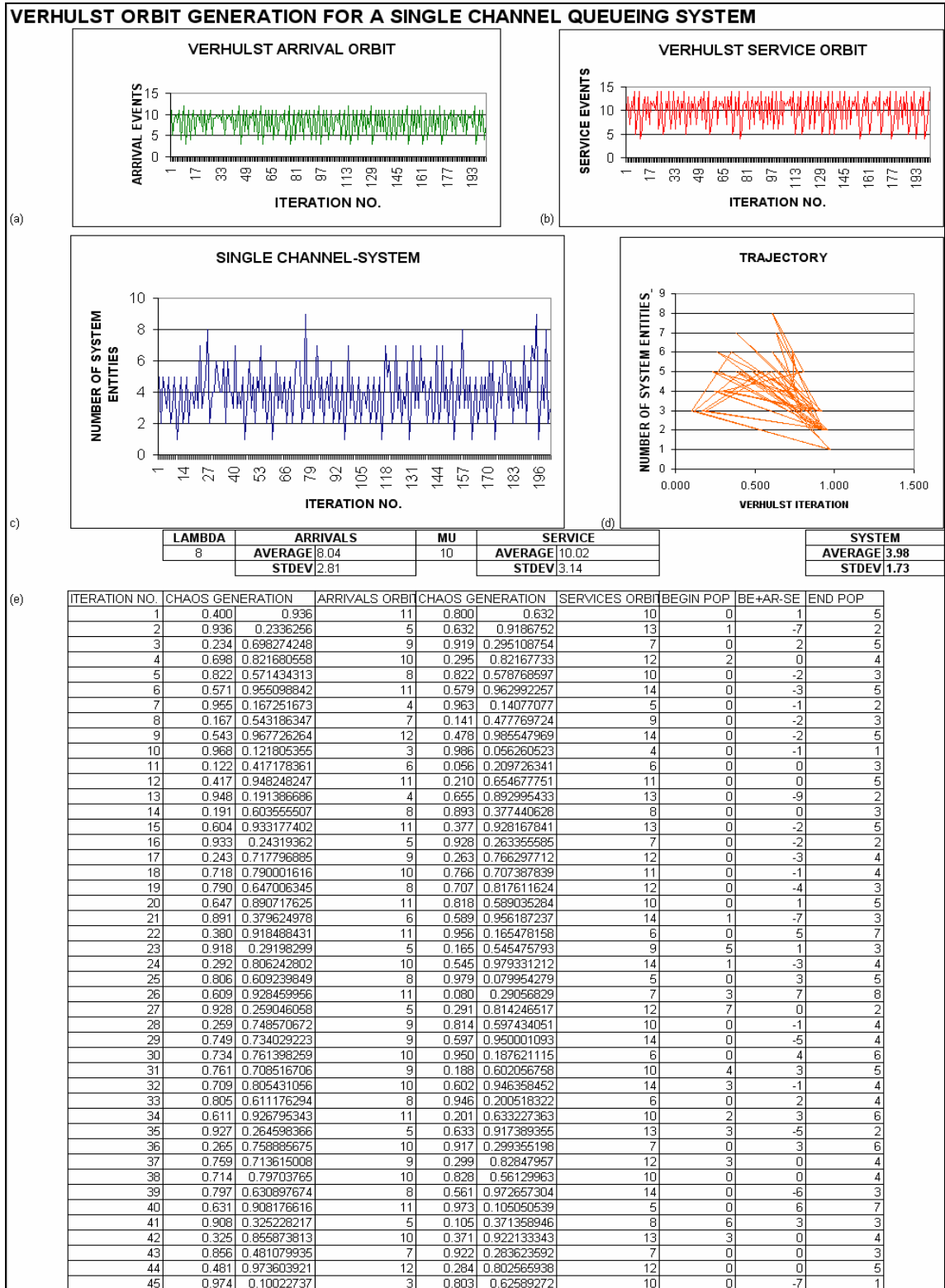


Fig. 6.2.3 GENERATION OF THE ORBIT OF A VERHULST SINGLE CHANNEL QUEUEING SYSTEM

6.2.4 Benchmarking the Verhulst generated single channel queue model

Comparison of the Poisson M/M/1 and Verhulst methods of generating system dynamics as depicted in Figs. 6.1.3 and 6.2.3 respectively results in

- achieving equivalence of mean and standard deviation values for the arrival and service processes,
- achieving graphical plausibility of system orbit likeness i.e. applying the TLAR criterion (“that looks about right”) in comparing the two system entity orbits.

No quantitative justification for “Poissonness” other than the foregoing parameter determination and application of the TLAR plausibility criterion has been carried out.

As a further matter of interest the Verhulst methods of generating system dynamics over 200 one minute intervals are shown in Fig. 6.2.4 for a **general service distribution** queueing system for $\lambda = 8, \mu = 10$ and $\sigma = 0.010$. The average number of entities in the system is given by:

$$L = L_q + \rho \quad (6.6)$$

$$\text{for } L_q = \frac{\lambda^2 \sigma^2 + \rho^2}{2(1 - \rho)} \quad (6.7)$$

$$\text{and } \rho = \frac{\lambda}{\mu} \quad (6.8)$$

where:

L = the average number of entities in the system

L_q = the average number of entities in the queue

ρ = the traffic intensity

λ = the average number of arrivals entering the system per unit time

σ^2 = the variance of the service time

μ = the average number of services offered per unit time

The results indicate

- achieving equivalence of mean and standard deviation values for the arrival and service processes,
- achieving graphical plausibility of system orbit likeness i.e. applying the TLAR criterion in comparing the two system entity orbits.

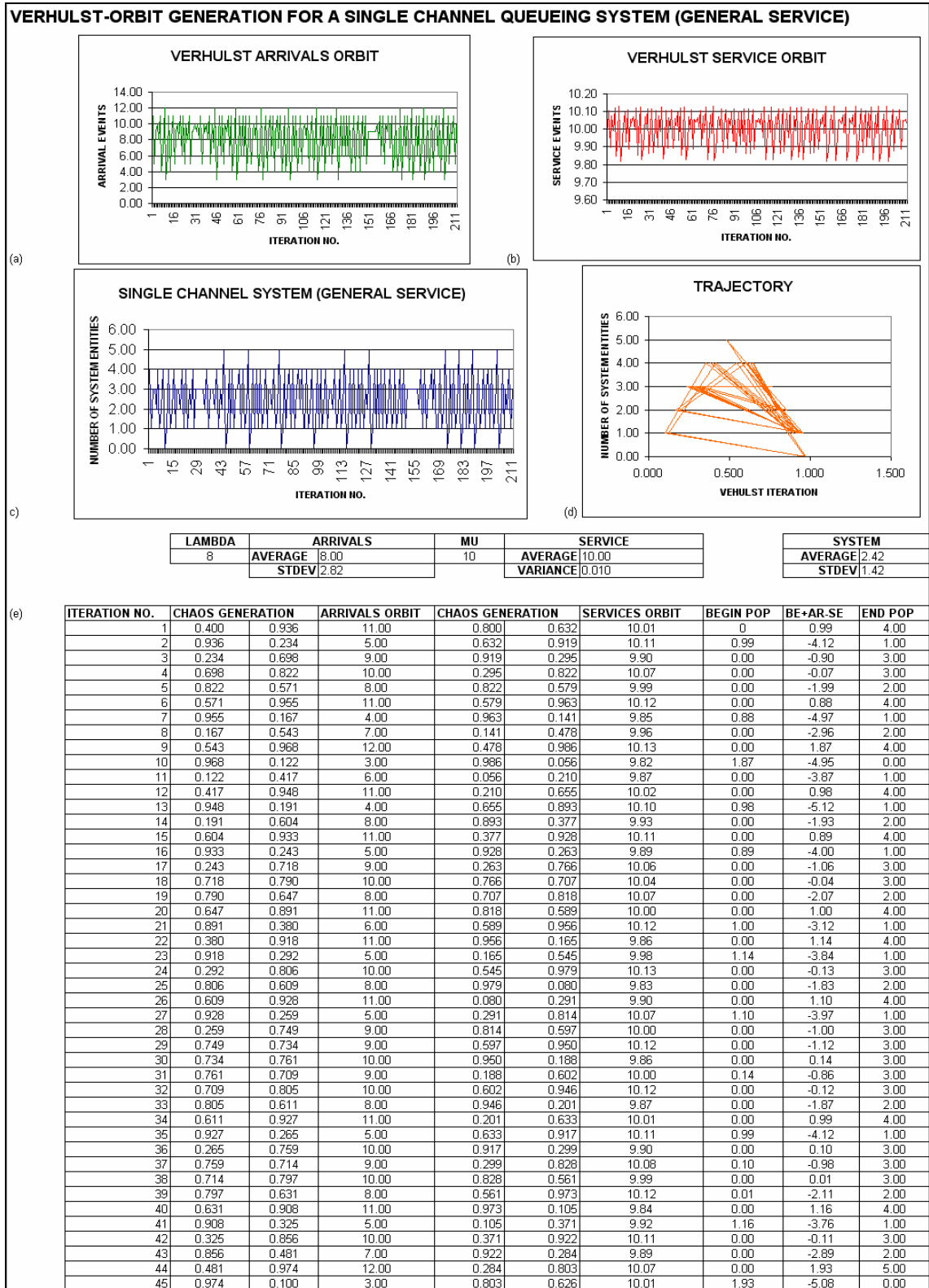


Fig. 6.2.4 GENERATION OF THE ORBIT OF A VERHULST QUEUEING SYSTEM (GENERAL SERVICE DISTRIBUTION)

6.2.5 Extending the Verhulst generated single channel queue model to deal with variable traffic intensity

Having achieved a degree of likeness greater than a scant semblance between the classical M/M/1 and Verhulst queueing system one may embark on extending the Verhulst model to include a range of traffic intensities which may prove to be beneficial in analysing the transient (dynamic) and steady state operation of a single channel queue.

Consequently the Verhulst queueing system has been extended to include a range of average arrival rates ($0.2 \leq \lambda < 1$) for an average service rate $\mu = 10$.

$$\text{Traffic intensity } \rho = \frac{\lambda}{10}$$

An example of a Verhulst generated single channel queue for a chronological sequence of values of λ of 9.8; 8.0; 9.5; and 7.0 over 200 one minute intervals is shown in Fig. 6.2.5.

Each of the chronological values of λ are employed for four consecutive epochs of 50 consecutive intervals.

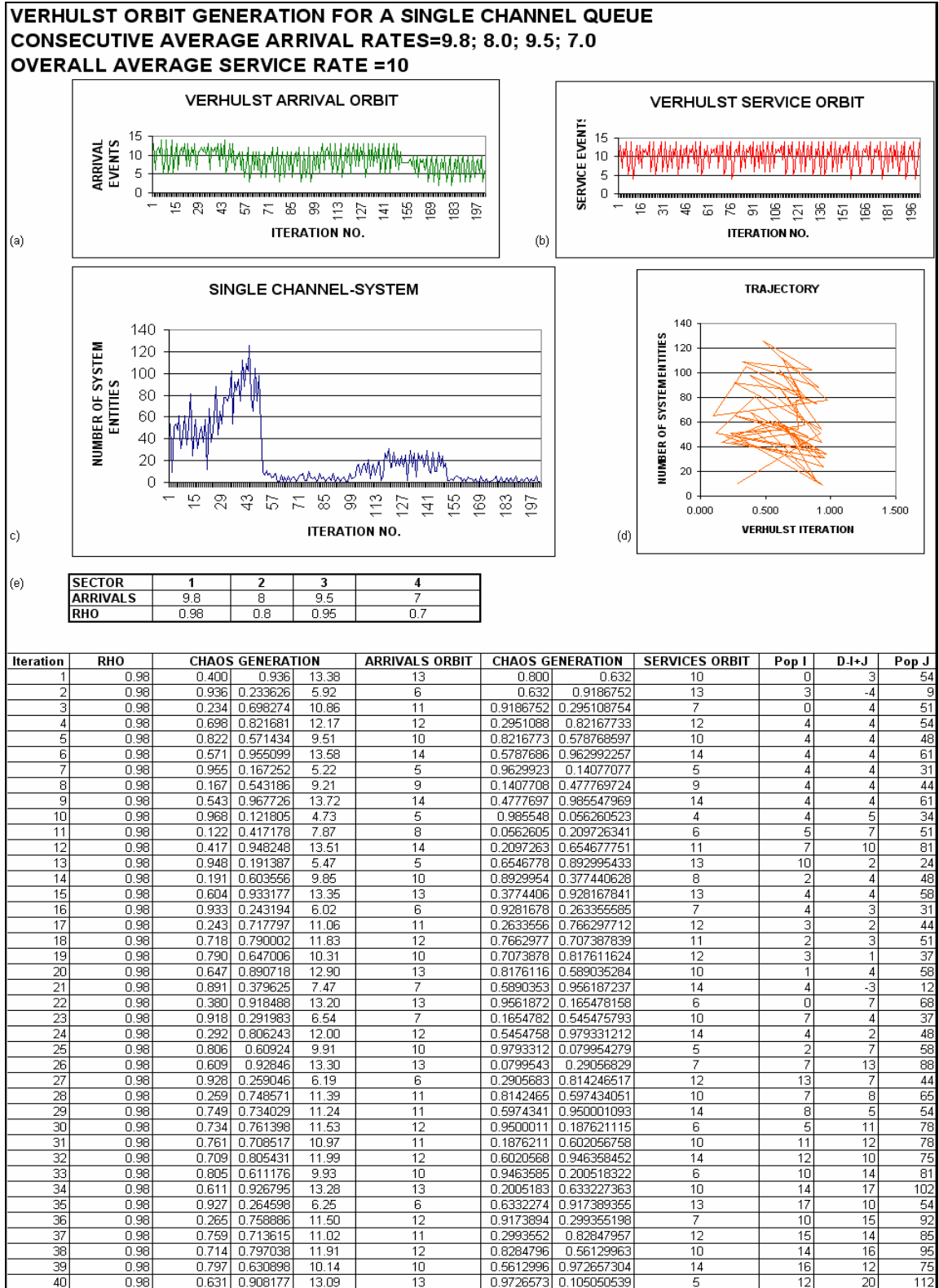


Fig. 6.2.5 GENERATION OF THE ORBIT OF AN EXTENDED VERHULST SINGLE CHANNEL QUEUE

The system orbit generated for a total of 200 one minute consecutive intervals unambiguously displays how the system behaves dynamically in a natural sense to being subjected to step functions in average arrival rate, albeit that the transitions from one steady state to a following steady state are ephemeral.

The extended model is versatile and amenable to use of many values of traffic intensity which may occur in practical situations. Such traffic intensity values may be selected a priori by external control or by automatically adjusting the arrival and service processes by means of internal system feedback mechanisms.

6.3 Further examples of Chaos generation

The introduction to Chaos generating methods described in par. 6.2 makes mention of other methods of mapping which may be considered as alternatives to Verhulst logistic mapping i.e.

- Weibull based mapping, and
- Trigonometric mapping. (Stewart [38])

The general modelling approach used for the generation of orbits for the two above- mentioned methods of mapping slavishly follows the underlying mathematical regimen employed in par.6.2.

The results which have been achieved are shown in :

- Fig. 6.3.1: Generation of the orbit of Weibull arrival events
- Fig. 6.3.2: Generation of the orbit of Weibull service events
- Fig. 6.3.3: Generation of the orbit of a Weibull single channel queueing system
- Fig. 6.3.4: Generation of the orbit of Sin arrival events
- Fig. 6.3.5: Generation of the orbit of Sin service events
- Fig. 6.3.6: Generation of the orbit of a Sin single channel queueing system.

The orbits shown have all been prepared for an average arrival rate of $\lambda = 8$ and an average service rate of $\mu = 10$.

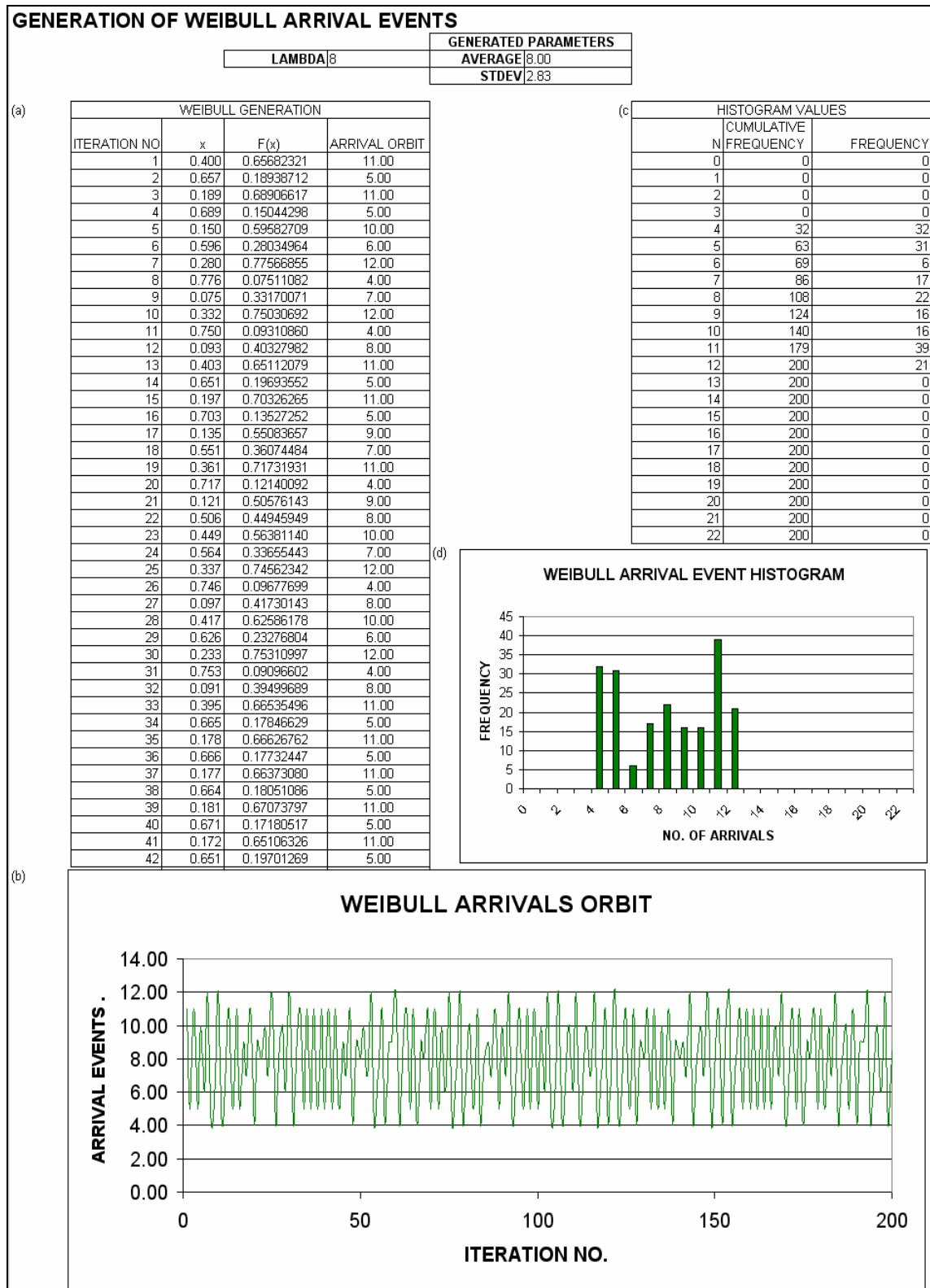


Fig. 6.3.1 GENERATION OF THE ORBIT OF WEIBULL ARRIVAL EVENTS

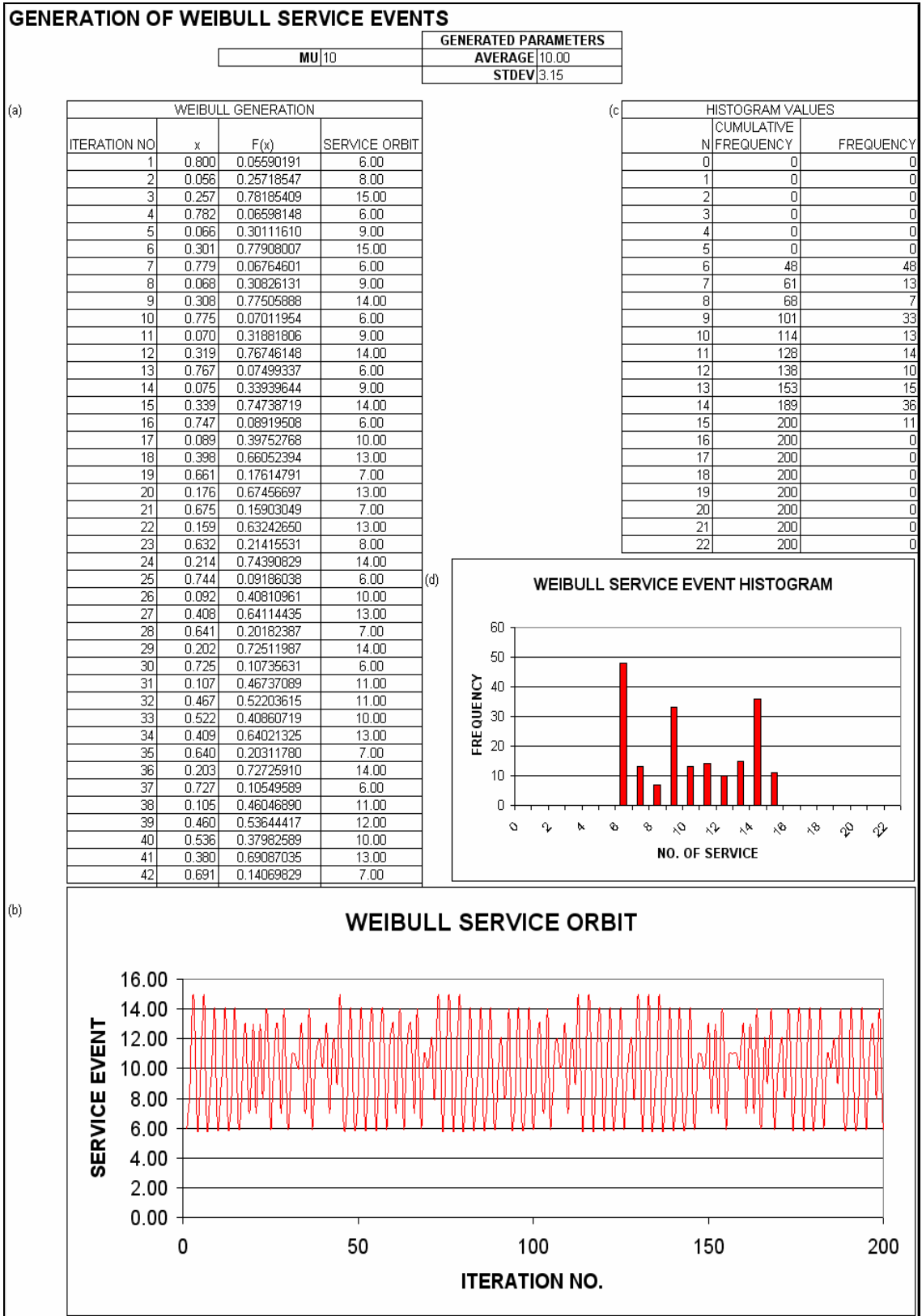


Fig. 6.3.2 GENERATION OF THE ORBIT OF WEIBULL SERVICE EVENTS

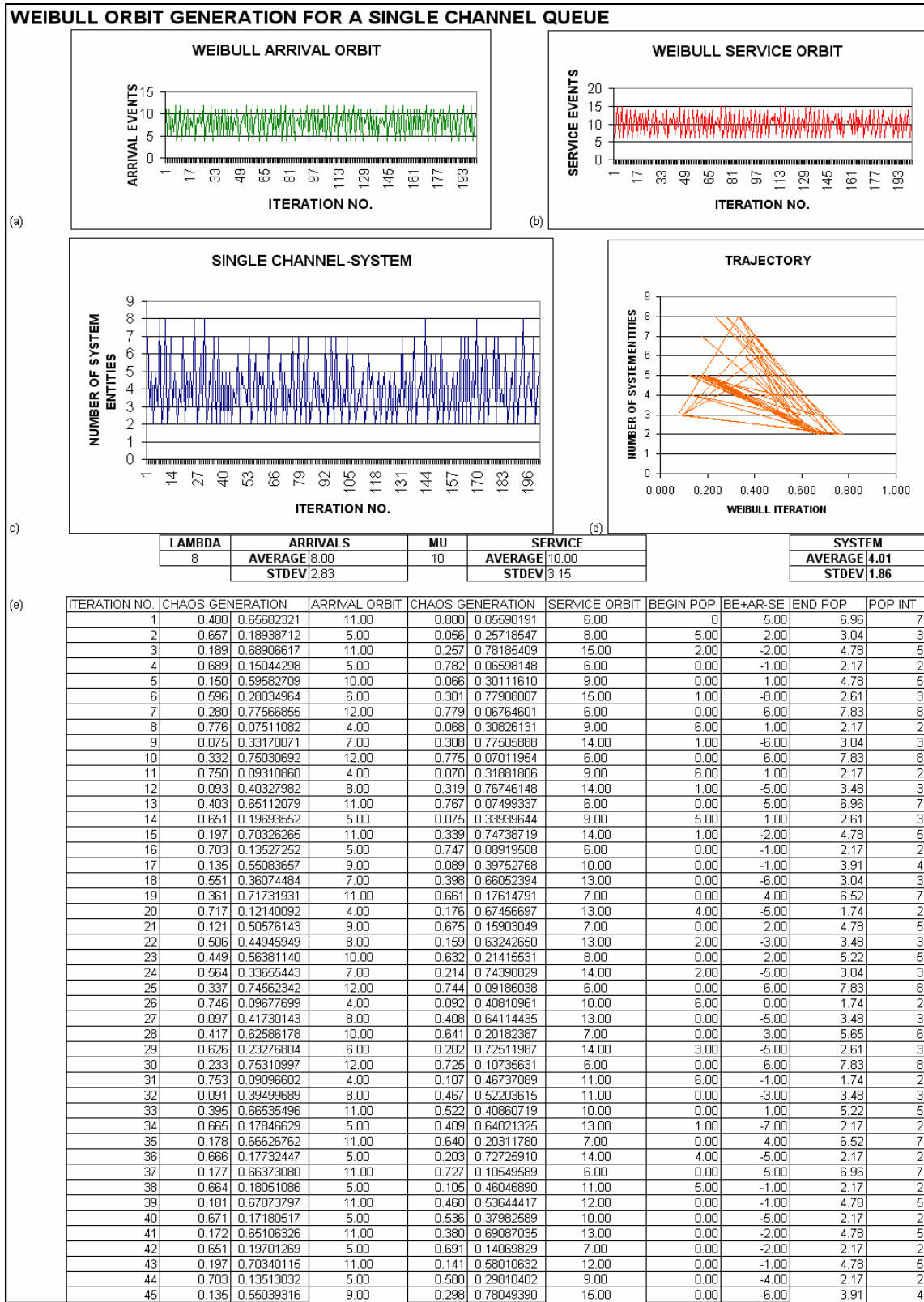


Fig. 6.3.3 GENERATION OF THE ORBIT OF A WEIBULL SINGLE CHANNEL QUEUEING SYSTEM

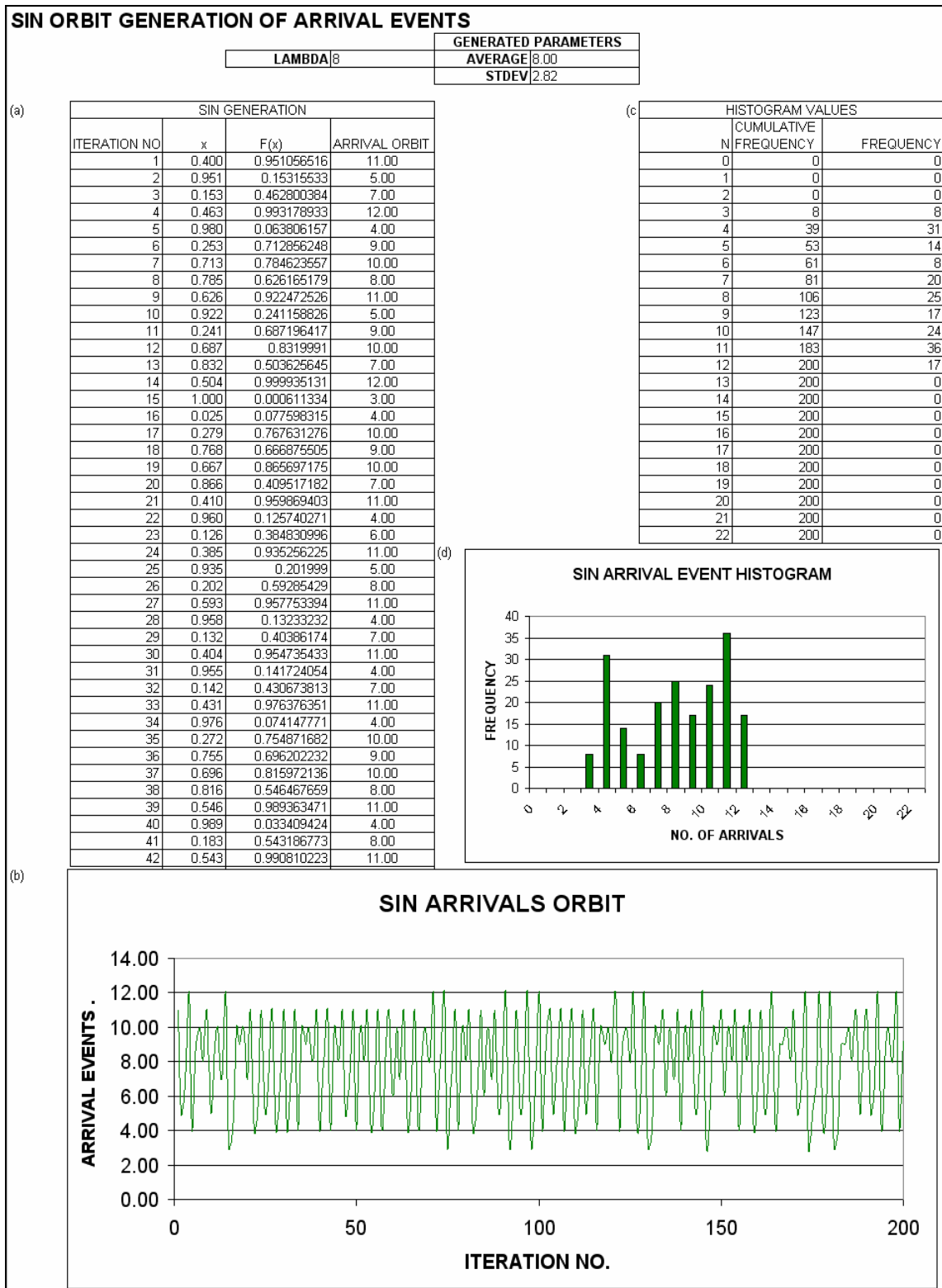


Fig. 6.3.4 GENERATION OF THE ORBIT OF SIN ARRIVAL EVENTS

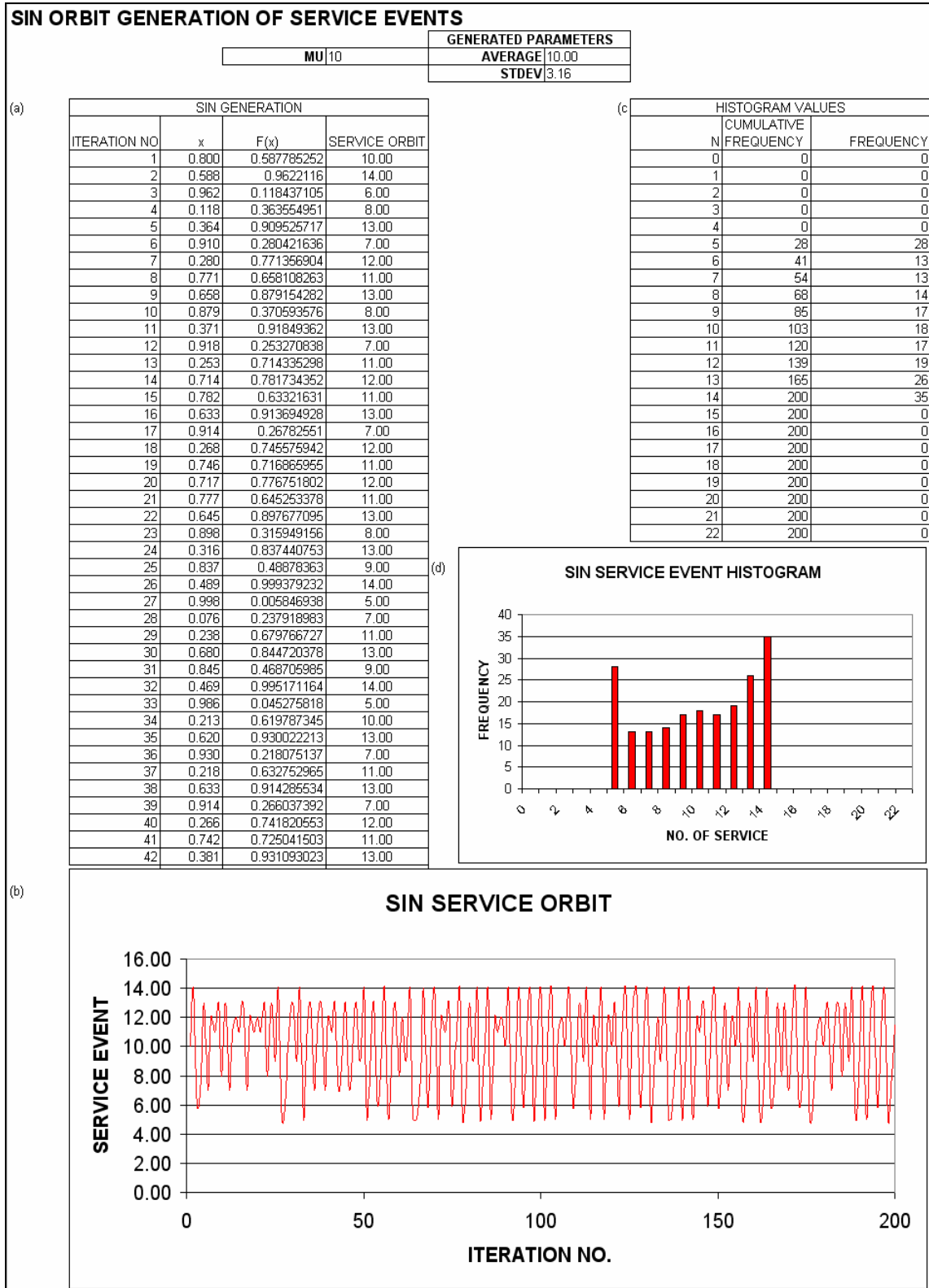


Fig. 6.3.5 GENERATION OF THE ORBIT OF SIN SERVICE EVENTS

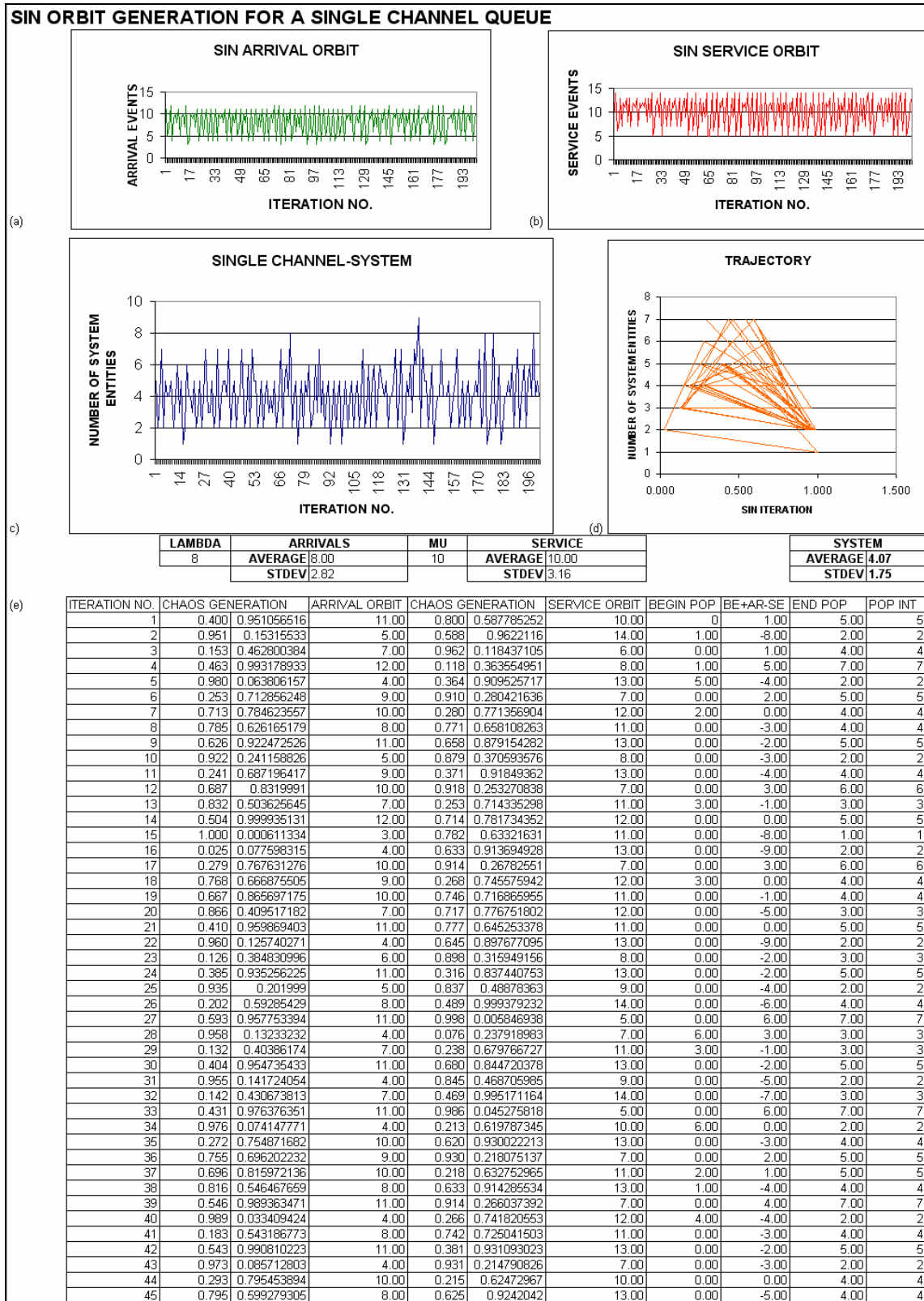


Fig. 6.3.6 GENERATION OF THE ORBIT OF A SIN SINGLE CHANNEL QUEUEING SYSTEM

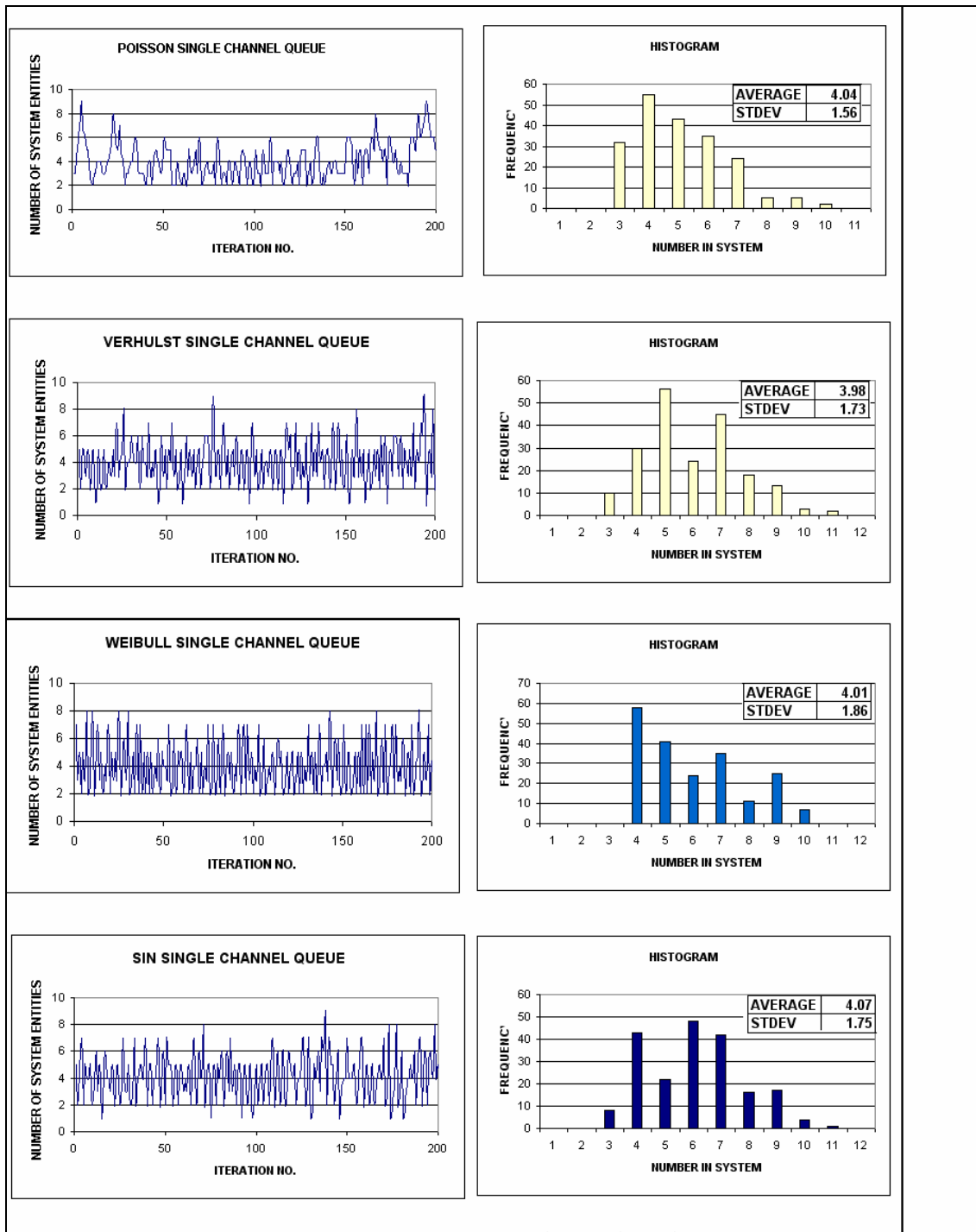


Fig. 6.3.7 PICTORIAL COMPARISON OF ORBITS OF SEVERAL SINGLE CHANNEL QUEUEING MODELS

6.4 Concluding remarks on single channel orbits resulting from a menu of methods of generation.

When viewing the various generated orbits shown in Fig. 6.3.7 one perceives that

- the various numerical values of average and standard deviation are virtually identical,
- one is inclined to believe that a measure of similarity exists in the histograms, and
- one consequently cautiously harbours the suspicion that **further extension and embellishment of the concept of chaos based system orbit generation** to match examples from the plethora of practical complex Systems of Congestion which exist, may be attempted.

The practical complex Systems of Congestion which are to be modelled in the following chapter are of a divergent nature and of necessity at least contain real time feedback rules to support decision making in achieving optimum transient and stable system operation.