Assessing Revenue Growth in Wireless Telecom under Production Uncertainty: An Approach of Modeling and Simulation

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Abstract
The local business environment of telecom industry in Manipur supports network reliability of wireless telecom at the expense of high input costs. The network reliability is a quality of service highly demanded by telecom users and it is regarded as business success parameter of the telecom firm. The production theory predicts that cost-benefit analysis becomes difficult in an environment where prices of input resources are rising at high and the firm is led to postpone the production or reduce the production investment. Production of reliable service at the expense of heavy cash outlays has resulted production uncertainty on the concept of negative return on investment. This paper is inspired by the mismatch between demand and supply of network reliability in the context of local business environment. This paper examines the behavior of wireless telecom network and employs a production function of a model network to study the economic growth behavior of the network under varying sets of input resources. In this paper, I make a simulation approach to generate empirical data for the traffic and other decision variables of the production function. The simulation model is trained to investigate network traffic as function of input resources such as diesel fuel, grid energy and network uptime and the information obtained from simulation is used in cost-benefit analysis of the production system. I find that there is meaningful revenue growth in the existing environment at 100 percent network uptime, which is desired for the highest level of network reliability.
Keywords: Economic growth; Production uncertainty; Local business environment; Network reliability

1. Introduction

Business environment of telecom service providers differs over space and the firm, which undertake economic activities with motivational objective of profit maximization by following uniform economic process irrespective of differing environments sometimes face challenges of production uncertainty. The production uncertainty, which leads to poor economic growth of the firm, is also influenced by lack of technological and market knowledge. In an environment where prices of the input resources are rising at high, cost-benefit analysis becomes difficult and consequently, the firm is led to postpone or reduce its investment on production of the service. However, it is indeed a paradox that high price in input resources often makes product differentiation that values the product and profit in long run in the market, which has attained oligopoly. From the neoclassical perspective on the firms' objective of profit maximization, the firms under any circumstances including production uncertainty must be profitable enough to cover cash outlays. Under this concept the firm has to take account of its cash flows and outlays in deciding how much to produce and supply. Researchers adopt various approaches to examine and analyze production processes in their effort to explore efficient techniques of production and overcome the uncertainty. Although extensive research has been done on uniform economic processes common to all business environments of the firm, there is lack of focus on the economic process that could yield substantial economic growth in the context of local environment. To help illustrate the necessity of undertaking such economic process and assist the firm's management in assessment of the cash flows and outlays under production uncertainty, a brief background of the wireless telecom service of Bharat Sanchar Nigam Limited Manipur is outlined, the context, which inspired this work. In managing uncertainty, Allan Afuah (2003) observes that whenever there is uncertainty, there is usually possibility of reducing it by acquisition of information and indeed, information is merely negative of uncertainty. In this paper, I construct a production function of a model wireless telecom network and describe approach for developing models for the decision variables with the help of which we could generate simulated data output of the model network. This simulated data provides flexible scope for examining changes in behavior of economic growth of the network under varying sets of input resources.

2. Background and Problem Definition

Economic growth of wireless network is the increase in production of traffic that is increase in the minutes of usage of the network. This traffic growth is characterized and stimulated by an important parameter called network reliability. Network reliability is a unique service quality of wireless network, which is regarded as key parameter for business success of telecom service providers (Meetei & Singh, 2014). In other sense, network reliability is assumed to have network availability as its foundation. This parameter however is often under threat as it is influenced by factors associated with internal management or external environment of the firm. In Manipur, the network availability of the wireless network is highly influenced by the environment in which the telecom industry operates. There is acute shortage of electrical grid supply at the base station sites of the wireless networks of the service providers. Although power supply is one of the critical challenges confronted by telecom operators worldwide, the situation differs over space. For example, non-availability of regular grid supply at the sites accounted for 70 percent of downtime in Nigeria (Ani & Emetu, 2013), while on average, 70 percent of the approximately 4,00,000 mobile towers in India face electrical grid outages in excess of 8 hours a day (Intelligent Energy, 2012). According to 2011 Economic Survey Manipur, published by Government of Manipur, there was a shortfall of 60 Megawatts when demand was 170 Megawatts in the year 2009-10 indicating electrical grid outage of 9 hours a day. However, the grid power availability at the base stations of the wireless network in Manipur was on average within four to six hours a day in the year 2012-13 (Meetei & Singh, 2014). This electrical grid outage of 18 hours a day has far exceeded the national average value of 8 hours a day. In the context of BSNL Manipur, 60 percent of the total network outage was due to inadequate power supply at the base stations (Meetei & Singh, 2014). According to primary sources obtained from base station sites and mobile switching center of BSNL, on average the wireless network registered 45 percent downtime in urban area while the figure was 55 percent in rural. The annual financial report 2011-12 of BSNL Manipur stated that in the financial year 2011-12, BSNL could get 73 percent of its total revenue from its wireless sector. Thus, wireless service sector is the major revenue-earning sector of BSNL Manipur, which has potential for further revenue growth as the present revenue of the network pertains to input resource of only 55 percent network availability. It has been suggested that non-availability of adequate electrical grid at the base stations is the main factor behind this high percentage of network outages. The diesel generators deployed at the base station sites are in fact incur large amount of fuel and operating expenses. Additionally, total monthly cash outflow is also influenced by other factors such as fuel losses and pilferage for which Intelligent Energy (2012) estimated a loss of 15 to 20 percent of the total diesel fuel consumption. Shutting down of the entire base stations during low traffic load is an approach being practiced by service providers to reduce energy consumption under the concept of dynamic management of network resources (Jossip, Tonko, & Goran, 2012). Various justifications have been put forth for the high percentage of downtime including a claim that high input cost on energy from diesel fuel in the absence of adequate electrical grid supply could lead to negative return on investment. This claim however appears to be less reasoning from standpoint of network reliability. The above discussions reveal that there is large capacity under-utilisation in the network as only 45 to 55 percent of the network's resource is used to generate major share of the revenue and further suggests that this resource under-utilisation is mainly because of production uncertainty. To examine the claimed justifications which prompted the uncertainty, this work uses the following questions: (i) Is there increase in return on investment with increase in network uptime using energy from diesel fuel? (ii) What is the production output of the wireless network at 100 percent network uptime? To answer these questions, we need experiments on the real network with large quantity of diesel fuel and other associated input resources however, due to fear of poor return on investement, this practice was not encouraged by the firm and as such, it had not opted for supply of adequate quantity of diesel fuel at base-stations. Gogg & Mott (1992) asserts, "Ideas which can produce considerable improvements are often never tried because of an employee's fear of failure" (as cited in Robinson, 2004). Many important managerial decision problems are too intricate to be solved by mathematical programming and experimentation with the actual system, even if possible, it is too costly and risky (Gupta & Hira, 2009).Simulation can be viewed as solution to both the off-line design and on-line operational management problems. Morris (1967) asserts, "Modeling is the enterprise of devising a simplified representation of a complex system with the goal of providing predictions of the system's performance measures of interest. Such a simplified representation is called a model. A model is designed to capture certain behavioral aspects of the modeled systems- those that are of interest to the analyst/modeler – in order to gain knowledge and insight into the system's behavior" (as cited in Benjamin & Tayfur, 2007). With a simulation, ideas can be tried in an environment that is free of risk. This can only help to encourage creativity in tackling problem situations (Robinson, 2004). Under the conditions of high input costs, risk and fear of poor return on investment, it is felt that modeling and simulation is an appropriate tool for solving the uncertainty since simulation offers the solution by allowing experimentation with the model of the system without interfering with the real system. In order to acquire information pertaining to cost-benefit analysis in the absence of real live data, the model introduced in this study uses network traffic as function of network availability in the process of production while various empirical data of the wireless network of BSNL Manipur set design aspects for the relevant parameters of the model.

3. Literature Review

This work draws on two distinct streams of literature. First, a brief review on economic growth of the wireless network is introduced. The economic growth concept, which forms conceptual idea of this study, is used to design a production function of the telecom network. Second, I describe the design aspects of the mathematical models of the decision variables of the production function. The logic applied in development of software for simulation is however discussed in the section- research concept and model formulation.

3.1 Economic Growth and Production Function

The inputs or resources called factors of production of the economic units are any commodities or services used to produce outputs such as goods or services. The way in which the inputs are combined in the process of making output is called technology and it can be depicted mathematically by the production function. The economic growth of a firm can be described with the help of production function, which is a relationship between inputs and output such that the inputs are combined in the most efficient way. Economic growth is generally derived from greater amount of inputs or from increase in productivity. Thus, increase in production input and increase in productivity are factors of economic growth. In addition to the increase in volume and productivity, other variables such as price and profitability are also widely used in productivity models where profitability is expressed as function of productivity, prices and volume such that Profitability = f (Productivity, Prices, Volume). The firm is said to be operating inefficiently if it is possible to produce more of the output with the same amount of inputs or if it is possible to produce same amount of output employing less of at least one input. When these situations are ruled out, we are left with only the efficient technique of production. The production function consists of only those techniques, which are efficient (Sen Anindya, 2014). The model of production function of the wireless network employed in this study has been widely used in the operations management and economics literatures. The production function that has been employed in this study for the network is the Cobb-Douglas production function and it is represented mathematically as

$$Q = A \times K^{\alpha} \times L_1^{\beta} \times L_2^{\delta} \qquad \ldots (1)$$

where, Q is network traffic, K is diesel fuel consumption, L_1 is grid energy consumption and L_2 is network uptime. The decision variables such as Q, K, L_1 and L_2 are functions of network uptime and A, α, β, δ are constant parameters. This study uses simulated data output of the decision variables as empirical data to derive these constant parameters and consequently to construct a production function of the wireless telecom network.

3.2 Network Traffic

Probability plays an important role in simulation just as it does in real life. Models of reasonable size and complexity exhibit a set of possible behaviors that, in general, are unknown unless the model is simulated. Models also have validity constraints that identify when they are good representations of the real world and when they contradict or incompletely describe the real system. In order to understand the range of possible behaviors, it would be useful to simulate the model under all possible conditions. However, this is impractical, except for the simplest model. Instead, practitioners use techniques such as Monte Carlo analysis (Barnett, 2003). This study uses Monte Carlo method of simulation where decision variables are represented by probabilistic distribution and random samples are drawn from the probability distribution using random numbers. The network traffic, which represents an important decision variable, is defined as ratio of the system occupation period to the total period of observation and it is expressed in *erlangs*. The average number of calls in progress on a network depends on both the number of calls that has arrived to the network and durations of the calls. The duration of a call is called its *holding time*. Therefore, traffic by a group of trunk is given by $A = Ch/T$, where A is traffic in erlangs, C is average number of call arrivals during time T and h is average holding time. The mathematical model of telecommunication traffic is assumed to have built up primarily from two major aspects of assumptions such as (a*) pure-change traffic* and (b) *statistical equilibrium*. In telecommunications, the call arrivals and call terminations are taken as random events under the assumption of the pure-chance traffic. Though the individual user does not make calls at random, the traffic in a telecommunications network however is the aggregate of the traffic generated by a large number of individual users connected to the network and such traffic in total generated by a large number of users is observed to behave as if calls were generated at random. Thus, the telecommunications traffic is characterized as a random process. The telecommunications traffic is also sometimes known as memoryless traffic as the call arrivals are independent random events and their occurrence is not affected by previous calls. Thus, the assumption of random call arrivals and terminations leads to the following results (Flood, 2011):

1. The number of calls arrivals in a given time has a Poisson distribution, i.e.:

   $$P(x) = \frac{\mu^x}{x!} e^{-\mu} \qquad (2)$$

   where, x is the number of call arrivals in time T and μ is the mean number of call arrivals in time T. For this reason, pure ch

2. The intervals, T, between the call arrivals are the intervals between independent random events and these intervals have a negative exponential distribution, i.e.:

   $$P(T \geq t) = e^{-t/\bar{T}} \qquad \ldots (3)$$

where, $\bar{T}$ is the mean interval between call arrivals.

3. Since the arrival of each call and its termination are independent random events and have a negative

exponential distributions, i.e.:

$$P(T \geq t) = e^{-t/h} \qquad \ldots (4)$$

where, h is the mean call duration (holding time).
The assumption of *statistical equilibrium* means that the generation of traffic is a stationary random process, i.e. probabilities do not change during the period being considered. Consequently, the mean number of calls in progress remains constant.

4. Research Concept and Model Formulation

Bharat Sanchar Nigam Limited Manipur launched its second-generation GSM (Global System for Mobile Communication) wireless telecom service in the year 2004. Since second-generation GSM sets the foundation for wireless network, this study considers the 2G GSM architecture. This network, which claims 75 percent stake of the total base-transceiver stations of BSNL Manipur, extends its service across the state including remote rural areas. The base station controller is housed in a central location where MSC is installed. The abis-interface is the communication link between BTS and BSC. BSNL uses either optical fiber or mini-link that is microwave radio media for connectivity between BTS and BSC. The base-transceiver station of the base station subsystem is one among the most energy-consumed units of the system and in addition, it has high outage probability.

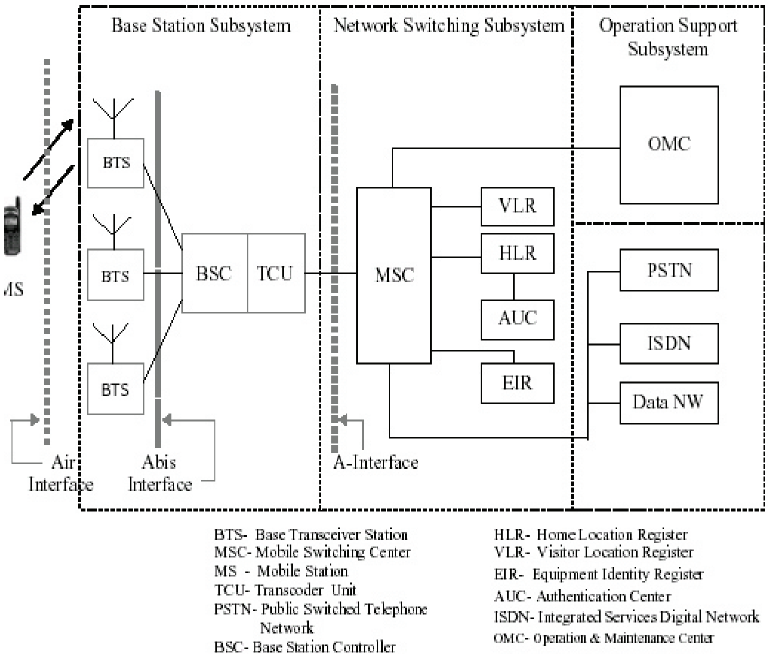

Figure 1: Architecture of 2G GSM Network

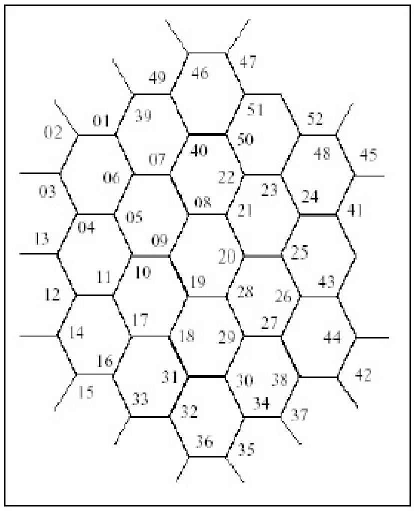

Figure 2: Model Wireless Network of 52 BTSs (2G GSM)

The network outage arises primarily from combination of lack of sufficient electrical energy at base stations, base-transceiver equipment fault, transmission equipment fault, mini-link fault, optical-fiber cable breakdown, poor supply chain system of diesel fuel, diesel generator fault, and power plant system fault. This work considers a network of 52 contiguous 2G GSM base-transceiver stations of Imphal city, the model production function of which is described in equation (1). This function has decision variables– namely *Q, K,* L_1 and L_2. The outage characteristics of the base-transceiver stations and the network's call handling behavior are two behavioral resources, which characterize conceptual idea as to how to develop models for the decision variables. The purpose of this function is to examine the behavior of economic growth of the network under varying sets of input resources.

4.1 Modeling Call Arrivals

One of the basic objectives of this study is to make a framework for modeling the network traffic at 100 percent of network uptime. The *number of call arrivals* and *holding times* (expressed in minute) of the calls are two parameters, which can represent the network traffic in terms of either *minutes of usage* or *erlangs*. The real-live traffic data in terms of *number of call arrivals* and *holding times* obtained from the network of 52 base transceiver stations is related to network uptime of only 45 to 55 percent. Although no attempt was made in real live situation to measure network traffic at 100 percent network uptime by providing large quantity of diesel fuel

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because of fear of possible heavy cash outlays on diesel fuel and negative return on investment, equation (2) and (3) however provide simulation design concept for the *number of call arrivals* and *holding times*.

BTS Name	Outage Sequence	BTS Name	Outage Sequence
A	B	A	B
07	1	40	27
04	2	48	28
19	3	52	29
08	4	30	30
16	5	38	31
10	6	33	32
24	7	46	33
21	8	36	34
25	9	13	35
09	10	14	36
15	11	39	37
18	12	42	38
23	13	43	39
01	14	44	40
17	15	31	41
37	16	47	42
11	17	49	43
22	18	50	44
29	19	51	45
26	20	41	46
34	21	03	47
32	22	05	48
45	23	02	49
12	24	06	50
28	25	20	51
35	26	27	52

Table 1: BTS Outage Sequence

Affected Base Station	No. of Affected Base Stations	Outage (%)	Expected Affected Calls	Real Affected Calls	Outage Impact Factor	Affected Base Station	No. of Affected Base Stations	Outage (%)	Expected Affected Calls	Real Affected Calls	Outa Impa Fact
A	B	C	D	E	F=E/D	A	B	C	D	E	F=E/
07	1	2	3	0	0.00	40	27	52	81	48	0.5
04	2	4	6	0	0.00	48	28	54	84	51	0.6
19	3	6	9	0	0.00	52	29	56	87	56	0.6
08	4	8	12	2	0.17	30	30	58	90	60	0.6
16	5	10	15	2	0.13	38	31	60	93	62	0.6
10	6	12	18	2	0.11	33	32	62	96	67	0.7
24	7	13	21	2	0.10	46	33	63	99	68	0.6
21	8	15	24	4	0.17	36	34	65	102	73	0.7
25	9	17	27	6	0.22	13	35	67	105	78	0.7
09	10	19	30	12	0.40	14	36	69	108	83	0.7
15	11	21	33	15	0.45	39	37	71	111	86	0.7
18	12	23	36	17	0.47	42	38	73	114	89	0.7
23	13	25	39	19	0.49	43	39	75	117	92	0.7
01	14	27	42	19	0.45	44	40	77	120	97	0.8
17	15	29	45	23	0.51	31	41	79	123	103	0.8
37	16	31	48	24	0.50	47	42	81	126	106	0.8
11	17	33	51	28	0.55	49	43	83	129	112	0.8
22	18	35	54	32	0.59	50	44	85	132	116	0.8
29	19	37	57	32	0.56	51	45	87	135	121	0.9
26	20	38	60	34	0.57	41	46	88	138	126	0.9
34	21	40	63	36	0.57	03	47	90	141	129	0.9
32	22	42	66	36	0.55	05	48	92	144	133	0.9
45	23	44	69	37	0.54	02	49	94	147	138	0.9
12	24	46	72	39	0.54	06	50	96	150	144	0.9
28	25	48	75	43	0.57	20	51	98	153	150	0.9
35	26	50	78	46	0.59	27	52	100	156	156	1.0

Table 2: Outage Impact Factor

The two variables of the equations– namely *mean number of call arrivals* and *mean holding time* could demonstrate as good parameters for estimation of *number of call arrivals* and *holding times*. The network model shown in figure 2, which consists of 52 BTSs (2G GSM) is used in this work to deduce *mean number of call arrivals* and *outage impact factor*. Table 1 provides the base-station outage probability sequence from highest to lowest that has been prepared from the base-station outage probability distribution depicted from the empirical outage data of the 52 base stations. The characteristic of the network is such that calls pertaining to the failed or down base stations are handled by the neighboring active base stations and calls are affected only when there is concurrent outage among the contiguous base stations. Therefore, the algebraic sum of the average number of expected call arrivals of the down base stations does not provide value for the average affected number of calls. In order to determine accurate value of the average number of call arrivals per base-transceiver station per hour, the network behavior and outage characteristic of the network is considered in this study. In computing average number of call arrivals, we consider all the base stations of the network whether the base station is active or not and thus, the average number of call arrivals is the average number of calls, which is expected to arrive in any of the base stations of the network including non-active base stations. From the behavior of the network, it is understood that during outage the number of affected calls is influenced by the number of down base stations, geographical locations of the base stations, base-station outage probability and average number of call arrivals. To deduce outage impact factors, each sector of the base station is assumed to have an average traffic of one call. Since there are three sectors in a base station, the average traffic per base station is three calls. In order to demonstrate how the calls are affected during outage, we may consider an example in which we assume that BTS08 and BTS21 fail to radiate in time duration of one hour. Under such outage condition, the affected number of calls is two and not six. This is due to non-radiation of the neighboring sectors 0821 and 2108. The traffic belonging to other affected sectors 0807, 0809, 2122 and 2120 are handled by neighboring active BTS and as such, there is no outage impact on the number of call arrivals. Now, if we assume that first 20 base stations of Table 1 fail to radiate then by virtue of the behavior of the network and outage probability characteristics of the base stations, the number of affected calls in real sense under this condition is 34. However, normally an outage impact of 60 calls was expected as number of affected call arrivals. The ratio of the *real number of affected call arrivals* to the *expected number of affected call arrivals* is termed in this work as *outage impact factor*. Thus, the outage impact factor at 38 percent of network outage (20 BTSs down) is 0.57. The outage impact factor of the network estimated according to the base stations outage probability is shown in Table 2. This outage impact factor together with number of call arrivals obtained from the empirical real live traffic data of the network is used in this work to deduce values of mean number of call arrivals. If $\boldsymbol{y}$ is total number of calls, which could arrive to the network in the time duration of one-hour, then from the following equation we can derive the real *mean number of call arrivals*.

$$y = A\,(1\text{-}\sigma)\,\mu + B\mu \qquad \dots (5)$$

No. of serving BTS	Uptime %	N/W Calls (Real)	Normal Calls (Expected)	Addl Calls served by Network	Uptime Impact Factor
A	B	C	D=A×3	E=C-D	F=E/D
52	100	156	156	0	0.00
51	98	156	153	3	0.02
50	96	156	150	6	0.04
49	94	156	147	9	0.06
48	92	154	144	10	0.07
47	90	154	141	13	0.09
46	88	154	138	16	0.12
45	87	154	135	19	0.14
44	85	152	132	20	0.15
43	83	150	129	21	0.16
42	81	144	126	18	0.14
41	79	141	123	18	0.15
40	77	139	120	19	0.16
39	75	137	117	20	0.17
38	73	137	114	23	0.20
37	71	133	111	22	0.20
36	69	132	108	24	0.22
35	67	128	105	23	0.22
34	65	124	102	22	0.22
33	63	124	99	25	0.25
32	62	122	96	26	0.27
31	60	120	93	27	0.29
30	58	120	90	30	0.33
29	56	119	87	32	0.37
28	54	117	84	33	0.39
27	52	113	81	32	0.40
26	50	110	78	32	0.41
25	48	108	75	33	0.44
24	46	105	72	33	0.46
23	44	100	69	31	0.45
22	42	96	66	30	0.45
21	40	94	63	31	0.49
20	38	89	60	29	0.48
19	37	88	57	31	0.54
18	35	83	54	29	0.54
17	33	78	51	27	0.53
16	31	73	48	25	0.52
15	29	70	45	25	0.56
14	27	67	42	25	0.60
13	25	64	39	25	0.64
12	23	59	36	23	0.64
11	21	53	33	20	0.61
10	19	50	30	20	0.67
9	17	44	27	17	0.63
8	15	40	24	16	0.67
7	13	35	21	14	0.67
6	12	30	18	12	0.67
5	10	27	15	12	0.80
4	8	23	12	11	0.92
3	6	18	9	9	1.00
2	4	12	6	6	1.00
1	2	6	3	3	1.00
0	0	0	0	0	0.00

Table 3: Uptime Impact Factor

where, $\boldsymbol{A}$ is the total number down BTSs, $\boldsymbol{\mu}$ is mean number of call arrivals per base station per hour, $\boldsymbol{\sigma}$ is outage impact factor and $\boldsymbol{B}$ is the number of serving base stations. Thus, by substituting real-live values of $\boldsymbol{y}$, $\boldsymbol{A}$, $\boldsymbol{B}$ and the outage impact factor, $\boldsymbol{\sigma}$ (corresponding to number of down/failed base stations) in equation (5), we can derive the value of the *mean number of call arrivals* for the time of one-hour duration. In simulation, we use this *mean number of call arrivals* together with *random numbers* to determine *number of call arrivals* of the base stations. Due to random nature of the calls as characterized by random numbers the values of the *number of call arrivals* of the base stations may differ from base station to base station. We may get the total number of call arrivals of the network by adding the *expected number of simulated call arrivals* of the individual serving base stations. However, in the event of outage of some base stations, the *real number of simulated call arrivals* of the network is not equal to the sum of the expected number of simulated call arrivals of serving base stations. This is because of the behavior of network and the outage characteristics of the base stations. To illustrate this, let us assume that 32 base stations of the network each carrying an average traffic of 3 calls radiate during a time of one hour duration. The expected total number of normal call arrivals under such uptime condition is 96 calls however, as per Table 3 the number of call arrivals is 122. This is due to network's call handling behavior and outage characteristics. So in order to make accounting of additional number of call arrivals in computing the *real number of simulated call arrivals* of the network at different uptimes, a new parameter called *uptime impact factor* is introduced. Table 3 shows values of the *uptime impact factors*, which are at different uptimes of the network. The *number of call arrivals,* $\boldsymbol{P}$ of a serving base station is therefore estimated as

$$P = P_{active} \times (1+k) \qquad \dots (6)$$

where, $\boldsymbol{k}$ is the uptime impact factor, $\boldsymbol{P_{active}}$ is expected number of simulated call arrivals of the serving base station.

Time Slot	Mean No. of Call Arrivals (x 100)	Mean Holding Time (Sec)
00	2	73
01	1	69
02	1	67
03	1	51
04	3	40
05	7	41
06	12	42
07	17	43
08	19	42
09	19	41
10	17	40
11	17	40
12	16	40
13	16	41
14	15	42
15	16	41
16	17	40
17	18	41
18	20	42
19	22	48
20	21	55
21	16	65
22	9	70
23	4	74

Table 4: Mean No. of Call Arrivals and Mean

Restore Time (Hour)	Random Number Interval	
01	0000	2211
02	2212	3934
03	3935	5275
04	5276	6320
05	6321	7134
06	7135	7768
07	7769	8261
08	8262	8646
09	8647	8945
10	8946	9999

Table 5: Restore Time and Random No. Intervals for MTTR=4 (Exponential Distribution)

Time Slot	Probability	Cumulative Probability	Random Number Interval		Outage Percent
00	0.0518	0.0518	0000	0517	72
01	0.0555	0.1073	0518	1072	77
02	0.0573	0.1646	1073	1645	79
03	0.0589	0.2235	1646	2234	81
04	0.0602	0.2837	2235	2836	83
05	0.0562	0.3399	2837	3398	78
06	0.0477	0.3876	3399	3875	66
07	0.0422	0.4298	3876	4297	58
08	0.0401	0.4699	4298	4698	55
09	0.0388	0.5087	4699	5086	54
10	0.0317	0.5404	5087	5403	44
11	0.0297	0.5701	5404	5700	41
12	0.0302	0.6003	5701	6002	42
13	0.0296	0.6299	6003	6298	41
14	0.0299	0.6598	6299	6597	41
15	0.0325	0.6923	6598	6922	45
16	0.0331	0.7254	6923	7253	46
17	0.0354	0.7608	7254	7607	49
18	0.0353	0.7961	7608	7960	49
19	0.0354	0.8315	7961	8314	49
20	0.0358	0.8673	8315	8672	49
21	0.0406	0.9079	8673	9078	56
22	0.0446	0.9525	9079	9524	62
23	0.0475	0.9999	9525	9999	66

Table 6: Network Outage Distribution

4.2 Traffic and Outage Data Gathering

No. of Call Arrivals (x 100)	007	008	009	010	011	012	013	014	015	016	017	018	019	020	021	022	023
Random No. Intervals	0000	0001	0004	0013	0033	0073	0147	0273	0472	0763	1164	1683	2318	3053	3861	4708	5555
	0000	0003	0012	0032	0072	0146	0272	0471	0762	1163	1682	2317	3052	3860	4707	5554	6364

No. of Call Arrivals (x 100)	024	025	026	027	028	029	030	031	032	033	034	035	036	037	038	039	040
Random No. Intervals	6365	7107	7760	8313	8763	9117	9385	9582	9721	9817	9881	9922	9948	9963	9972	9977	9980
	7106	7759	8312	8762	9116	9384	9581	9720	9816	9880	9921	9947	9962	9971	9976	9979	9999

Table 7: No. of Call Arrivals and Random No. Intervals for Mean No. of Call Arrivals= 22(x100) (Poisson Distribution)

The network traffic is expressed as function of network uptime as described in equation (1). The real live traffic data that is total number of call arrivals of the wireless network, which were at different uptimes in the past 330 days of period ending 31/03/2013, is used as value of y in equation (5) to estimate value of *mean number of call arrivals* and *mean holding time*. The number of call arrivals varies over time, for example, number of calls arrivals during 4am to 5am may not necessarily equal to the number of calls arrivals during 1pm to 2pm. Therefore, in this work a day is divided into 24 time slots, each having a time of one-hour duration. Table 4 shows the values of the *mean number of call arrivals* of the network which have registered in the 24 different time slots. These *mean number of call arrivals* are derived from the real live empirical traffic data of the network using equation (5). As described in equation (2), the number of call arrivals follows Poisson distribution and as such, the random number intervals derived from the Poisson probability distribution of the *mean number of call arrivals* is assigned against the *number of call arrivals* for future use and reference during simulation. For example, the *number of call arrivals* and *random number intervals* correspondence in respect of mean number of arrivals of value 22 is illustrated in Table 7. Table 4 shows the values of real *mean holding times* of the calls registered in the 24 time slots. The value of the mean holding time is computed from the real-live holding times of the network. As stated in equation (4), holding times follow negative exponential distribution and therefore exponential probability distribution is used in preparation of *holding time-random number intervals* correspondence from the mean holding time. The network and base station outage is viewed in this study from two aspects– (a) the outage durations of the base stations during same observed time may not necessarily equal to each other (b) the number of down base stations vary over time. *Mean time to restore (MTTR)* is an important decision variable in simulation and according to Chen Yachuan (2006), restore time is a random variable and it is often assumed to have an exponential distribution. MTTR is average fault restoration time. The value of MTTR is computed as 4 hours from the real live outage data of the network. The *restore times* and *random number intervals* correspondence in respect of the *mean time to restore* of value 4 is shown in Table 5. Another important parameter is network outage distribution and this outage distribution does not follow any standard probability distribution that is number of down base stations vary over time. In Monte Carlo Simulation, according to Jaisankar (2006), decision variables may not explicitly follow any standard probability distribution such as Normal, Poisson, Exponential etc. and as such, distribution can be obtained by direct observation or from past records. Therefore, an empirical outage probability distribution is constructed from the past real live outage data of the network. This outage probability distribution is shown in Table 6.

4.3 Mathematical Model for Base Station Energy Consumption

The base stations get energy from three sources– namely grid distribution, diesel fuel and energy conserved in the battery bank. Telecom service providers install one or more base-transceivers at the base station sites. The base station and network switching system of the respective base-transceivers installed at the base station sites generate outage event reports of the base-transceivers. Meetei & Singh (2014) used these outage events in management of base-station energy consumption and deduced the following equations to measure quantity of diesel fuel consumption at the base station sites.

P_{2G}, P_{3G}, P_{CDMA}, P_{WIMAX}, P_{TRANS}, and P_{BASIC} are average power consumption rates of 2G BTS, 3G BTS, CDMA

Total power consumption, P_{SITE} :

$$P_{SITE} = P_{WLOAD} + P_{INFRA}$$

where, $P_{WLOAD} = \sum_{i=1}^{n} P_{2Gi} + P_{3G} + P_{CDMA} + P_{WIMAX}$; $\quad P_{INFRA} = \sum_{j=1}^{m} P_{TRANSj} + P_{BASIC}$

BTS, WiMax, Transmission equipments and Landline exchange respectively; ***n*** represents numbers of 2G BTS, ***m*** represents number of transmission equipment.

Backup factor, α:

$$\alpha = \frac{\sum_{k=1}^{q} P_{PPMk} - P_{SITE}}{P_{SITE} \times 100} \times \rho$$

where, P_{PPM} is power supply capacity in Ampere of the individual SMPS (switched mode power supply) modules, ***q*** is the number of SMPS modules and ***ρ*** is a energy conservation factor.

Energy obtained from grid power supply, E_{ELECT} (in AH):

$$E_{ELECT} = (P_{SITE} \times t_{ELECT}) + \alpha \times P_{SITE} \times t_{ELECT} \times \beta$$

where, t_{ELECT} is the total hours of grid power availability. If there is no charging of battery, $\beta = 0$ else $\beta = 1$.

Total energy consumption, E_{SITE} (in AH):

$$E_{SITE} = P_{WIMAX} \times t_{WIMAX} + P_{3G} \times t_{3G} + \sum_{i}^{n} P_{2Gi} \times t_{2G} + P_{CDMA} \times t_{CDMA} + P_{INFRA} \times t_{INFRA}$$

Energy obtained from Diesel Generator, E_{DG}:

$$E_{DG} = \frac{E_{SITE} - E_{ELECT}}{1+\alpha} \quad , \text{if } E_{DG} < 0,\ E_{DG} = 0$$

DG run hour, t_{DG}:

$$t_{DG} = \frac{E_{DG}}{P_{SITE}}$$

Total diesel fuel consumption, F_{SITE}:

$$F_{SITE} = t_{DG} \times F_{DG}$$

where, F_{DG} is the hourly diesel fuel consumption rate (in litres) of the diesel generator.

where ,t_{WIMAX}, t_{3G}, t_{CDMA}, t_{2G} and t_{INFRA} are total uptime hours of WiMax, 3G-BTS, CDMA-BTS, 2G-BTS and landline exchange/transmission equipment respectively..

4.4 Research Process and Data Flow

This study considers network availability as broader concept of network reliability. Network reliability is a service quality of the network, which is regarded as key parameter for business success of the wireless sector of the telecom service providers. Since network uptime sets foundation for network availability all the decision variables– namely *Q, K,* L_1 *and* L_2 of the production function are modeled as functions of the network uptime.

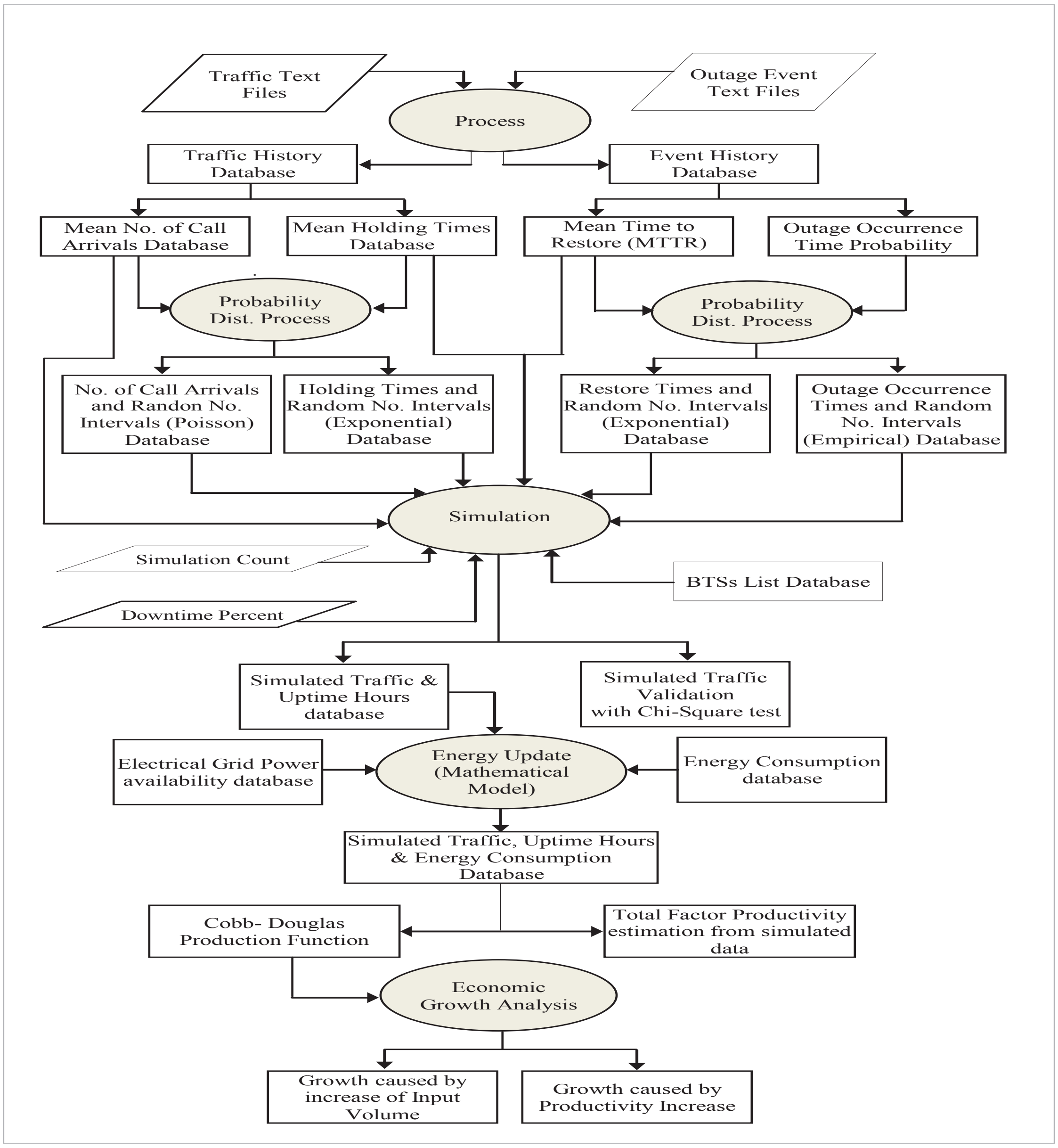

Figure 3: Research Process and Data Flow

In this section, I describe the steps of research process and subsequently logics applied in development of the research process and simulation software. In broad sense, this approach is based on development of software, which is trained to investigate network traffic *(Q)* as a function of diesel fuel *(K)*, grid energy (L_1) and network uptime (L_2). Figure 3 shows the schematic block diagram of the research process. Using equation (6) we can compute the number of call arrivals, *P* which would arrive to the network at different times. The holding times of the number of calls arrivals are not same and as such the simulated traffic in terms of minutes of usage (MOU) of the time slots described in the figure 3 is the sum of the holding times of all the individual calls computed using equation (6). Thus, the simulated traffic is the sum of the traffics in minutes of usage carried by the network in its 24 different time slots of a day. The simulated mean number of call arrivals is validated with the real-live mean number of call arrivals using Chi-square test. Figure 4 shows a part of the schematic block diagram of the traffic generation process. The number of serving base stations that determines network availability over the 24 time slots of the day is computed using network outage probability distribution shown in Table 6 and the downtime percent.

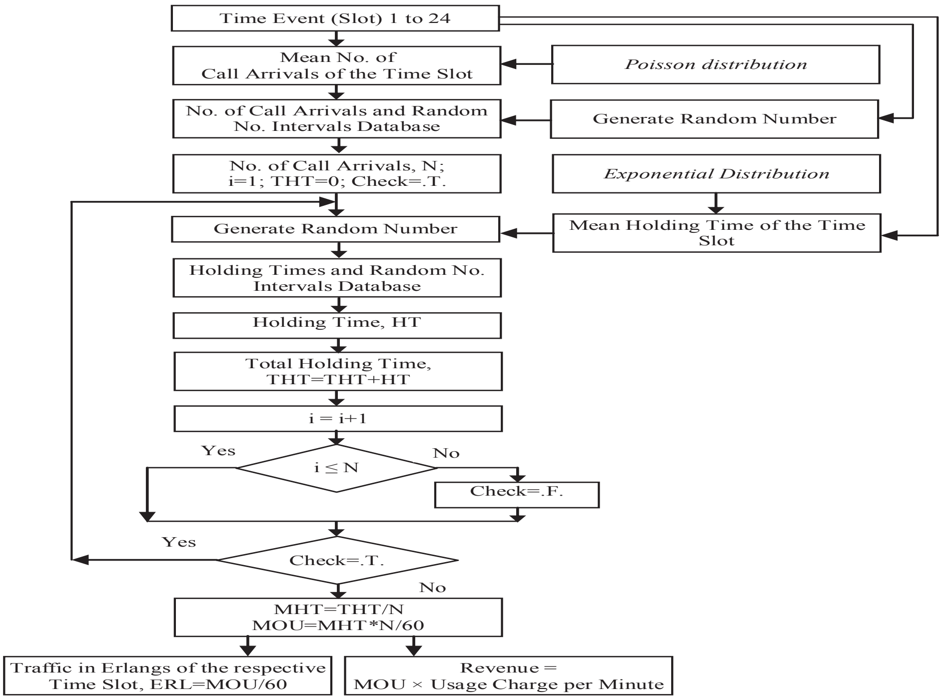

Figure 4: Traffic Generation Process

The different types of equipments such as base-transceiver station, transmission equipment, landline etc. housed in the base-station sites have different energy consumption rates. With the help of energy consumption database and the mathematical model for base-station energy consumption discussed in section 4.3, we could compute the quantity of diesel fuel consumption in litres and grid energy consumption in kWh (kilowatt- hour) at the base station site during network availability period of the day.

5. Data Analysis and Estimation of Production Function

5.1 Traffic Validation

The network traffic per base station per hour expressed in erlangs is used in this study as parameter for validation of the simulated traffic. Chi-square test is employed as main verification technique to validate the traffic. Simulation runs are conducted with the input variables such as simulation count, mean call arrivals, mean time to restore, mean holding time, uptime percent etc. to generate empirical traffic data for construction of the production function. The simulated traffic output of the 24 time slots of the day is taken as observed/ predicted value for the Chi-Square test. The Chi-square test is employed either to reject or to accept the hypothesis– "predicted value of traffic (simulation) is equal to expected value of the traffic (real)". The expected value of the traffic, A in erlangs is computed analytically from the real *number of call arrivals* and *holding times* using the equation, $A = Ch/3600$ where, C is number of call arrivals during *3600* seconds (one hour) and ***h*** is the holding time in seconds. The expected value of traffic is compared with the value of traffic generated from 51 simulation runs under the Null and Alternate hypotheses given below.

H_0: The predicted value of traffic (simulation) is equal to expected value of traffic. *(Null Hypothesis)*

H_1: The predicted value of traffic (simulation) is not equal to expected value of traffic. *(Alternate Hypothesis)*

α = 0.05 level of significance for testing these hypotheses

Time Slot	Chi-Square for Traffic	Chi-Square value at 0.05 level significance	Null Hypothesis
01:00	48.04	67.51 (50 df)	Accepted
02:00	36.06	67.51 (50 df)	Accepted
03:00	40.04	67.51 (50 df)	Accepted
04:00	41.16	67.51 (50 df)	Accepted
05:00	65.72	67.51 (50 df)	Accepted
06:00	60.45	67.51 (50 df)	Accepted
07:00	56.88	67.51 (50 df)	Accepted
08:00	54.11	67.51 (50 df)	Accepted
09:00	59.24	67.51 (50 df)	Accepted
10:00	62.78	67.51 (50 df)	Accepted
11:00	49.27	67.51 (50 df)	Accepted
12:00	65.44	67.51 (50 df)	Accepted
13:00	58.67	67.51 (50 df)	Accepted
14:00	56.34	67.51 (50 df)	Accepted
15:00	39.85	67.51 (50 df)	Accepted
16:00	60.12	67.51 (50 df)	Accepted
17:00	56.43	67.51 (50 df)	Accepted
18:00	50.97	67.51 (50 df)	Accepted
19:00	61.35	67.51 (50 df)	Accepted
20:00	48.65	67.51 (50 df)	Accepted
21:00	60.08	67.51 (50 df)	Accepted
22:00	52.54	67.51 (50 df)	Accepted
23:00	42.64	67.51 (50 df)	Accepted
24:00	56.62	67.51 (50 df)	Accepted

Table 7: Chi- Square for Hourly Traffic

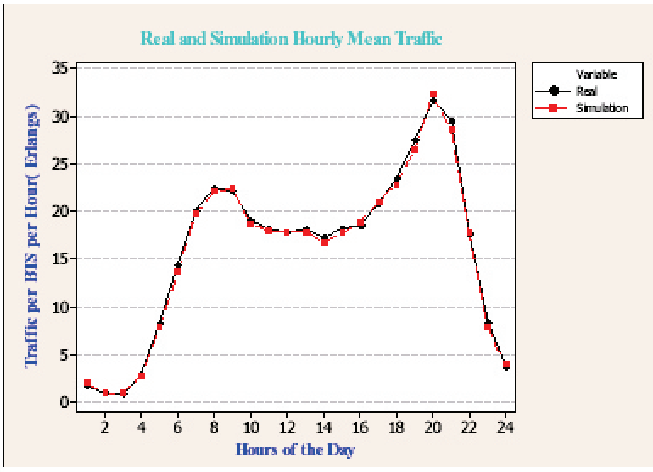

Figure 5: Real and Simulation Mean Traffic

If Chi-Square value of traffic of the individual time slot is less than the table value of Chi-Square at 0.05 levels of significance with (n-1) degree of freedom where n is the number simulation runs (i.e. simulation count =51 in this case), then the hypothesis is accepted else it is rejected. The result as shown in Table 7 supports the null hypothesis.

5.2 Production Function of the Model Network

In this study, we conduct 30 simulation runs for each of the input uptime percentage and the average value of these simulation runs is used as simulation output of the production day. This process is conducted for 18 different uptime inputs to get simulation outputs for 18 production days. The values of simulation output of the 18 different production days are illustrated in the Table 8. Kendrick method of total factor productivity (TFP) described by the equation $TFP = Q/(rK+wL_1+yL_2)$ where r, w, and y are the unit price values of K (diesel consumption in *litre*), L_1 (grid energy in *kilowatt-hour*, *kWh*), and L_2 (uptime in *hour*) respectively is employed to estimate total factor productivity of the network. The unit prices of diesel fuel per litre and grid energy per kilowatt-hour (kWh) are assumed as INR 50 and INR 6 respectively. The unit operating cost per uptime hour per base station denoted by $\boldsymbol{y}$ in the equation is estimated from the operational expenditure of the firm. Purchase of diesel generator, battery bank, PIU (Power Interface Unit) and SMPS constitute the capital expenses, CAPEX and therefore, any kind of capital expenses is not considered in estimation of total factor productivity in this study. The operating expenses, OPEX is the monthly expenses incurred in running and maintaining equipments and other infrastructures housed in the telecom sites. Costs involved in some units of the infrastructure of the network such as (a) repair costs of diesel generator, (b) repair costs of power plant, (c) maintenance costs of battery bank, (d) transportation costs for refilling the diesel oil at the site, and (e) Optical fibre cable maintenance & repair costs are considered as OPEX. From the OPEX made by the firm during January 2013 to June 2013, the maintenance cost per hour per base station is estimated as INR 22. Using unit prices of diesel, grid energy and operating cost as INR 50, INR 6 and INR 22 respectively, we can calculate TFPs of the 18 production days as illustrated in Table 8.

Production Day	Energy Consumption by Wireless Equipment (AH)	Infra Energy Consumption (AH)	Total Energy Consumption (AH)	Electrical Energy from Grid (AH)	Electrical Energy from Grid (kWh)	Energy from Diesel Generator (AH)	Diesel Consumption by Diesel Generators (Litres)	Total Uptime (Hours)	Total Downtime (Hours)	Percentage of Uptime	Day's Traffic (Erlangs)	Total Factor Productivity
A	B	C	D=B+C	E	F=(E×48)/1000	G	H	I	J	K=(I×100)/(I+J)	L	M
1	13743.00	13754.00	27497.00	19542.70	938.05	3608.80	169.10	329.00	919.00	26.36	5571.00	15.68
2	14819.00	13732.00	28551.00	20740.86	995.56	3635.10	166.20	340.00	908.00	27.24	5752.00	15.86
3	13683.00	13799.00	27482.00	20920.94	1004.21	3027.41	142.30	324.00	924.00	25.96	5166.00	15.29
4	14112.00	13776.00	27888.00	19757.96	948.38	3733.76	170.10	330.00	918.00	26.44	5068.00	14.17
5	15976.00	13951.00	29927.00	21779.04	1045.39	3716.24	177.20	381.00	867.00	30.53	6091.00	15.54
6	17541.00	14118.00	31659.00	21540.86	1033.96	4655.11	219.30	417.00	831.00	33.41	6635.00	15.11
7	22025.00	14388.00	36413.00	23480.94	1127.09	6008.35	280.70	520.00	728.00	41.67	8355.00	15.55
8	24127.00	14611.00	38738.00	24302.94	1166.54	6720.15	318.80	572.00	676.00	45.83	8777.00	14.82
9	26304.00	14796.00	41100.00	25125.12	1206.01	7447.08	354.40	624.00	624.00	50.00	9299.00	14.42
10	28496.00	14981.00	43477.00	25903.12	1243.35	8200.87	390.30	676.00	572.00	54.17	10066.00	14.43
11	30688.00	15166.00	45854.00	26681.12	1280.69	8954.63	426.40	728.00	520.00	58.33	10901.00	14.53
12	35072.00	15536.00	50608.00	28226.89	1354.89	10467.14	500.50	832.00	416.00	66.67	12436.00	14.5
13	37264.00	15721.00	52985.00	28898.78	1387.14	11273.64	538.20	884.00	364.00	70.83	13428.00	14.73
14	39456.00	15906.00	55362.00	29515.78	1416.76	12110.08	578.80	936.00	312.00	75.00	14602.00	15.1
15	41648.00	16091.00	57739.00	30079.98	1443.84	12970.42	619.00	988.00	260.00	79.17	15036.00	14.71
16	43840.00	16276.00	60116.00	30564.98	1467.12	13866.81	663.30	1040.00	208.00	83.33	15440.00	14.29
17	48224.00	16646.00	64870.00	31534.98	1513.68	15659.61	748.00	1144.00	104.00	91.67	16884.00	14.14
18	50416.00	16831.00	67247.00	31992.22	1535.63	16572.27	790.50	1196.00	52.00	95.83	17336.00	13.86

Table 8: Simulation Output of the Model Network

Network Size (No. of BTS)	Uptime Percentage	Diesel Consumption (Litres)	Energy from Grid (KWHr)	Uptime (Hour)	Diesel Energy Cost (INR)	Grid Energy Cost (INR)	Operating Cost (INR)	Total Input Cost (INR)	Output Traffic (Erlangs)	Output Traffic in MOU	Output Cost (INR)	Total Factor Productivity
		K	L1	L2	rK	wL1	yL2	rK+wL1+yL2	Q	Q×60	(MOU × 55)/100	TFP
52	40	272.33	1104.46	499.20	13616.36	2995.20	10982.40	27593.96	7781.36	466881.55	256784.85	14.95
52	50	361.68	1189.07	624.00	18084.20	3744.00	13728.00	35556.20	9533.21	571992.47	314595.86	14.69
52	55	406.36	1231.38	686.40	20318.12	4118.40	15100.80	39537.32	10410.09	624605.68	343533.12	14.59
52	60	451.18	1273.82	749.00	22559.20	4494.00	16478.00	43531.20	11294.03	677641.66	372702.91	14.52
52	70	540.68	1358.57	874.00	27034.20	5244.00	19228.00	51506.20	13077.95	784677.09	431572.40	14.42
52	80	630.18	1443.32	999.00	31509.20	5994.00	21978.00	59481.20	14893.36	893601.46	491480.80	14.38
52	90	719.68	1528.07	1124.00	35984.20	6744.00	24728.00	67456.20	16744.61	1004676.43	552572.03	14.38
52	100	808.47	1612.14	1248.00	40423.40	7488.00	27456.00	75367.40	18618.70	1117122.02	614417.11	14.40

Table 9: Input and Output Costs of the Network

Network Model	Initial Uptime	Input Costs (INR)			Economic Growth (INR)	Profitability (Surplus Value) INR	Return on Investment (ROI)	Productivity at 100% Uptime
		at Initial Uptime	at 100% Uptime	Increase in Input Costs (INR)				
52 BTS:24 Production Hours per Day	55%	39537	75367	35830	270884	235054	656%	14.40

Table 10: Economic Growth and Return on Investment

The values of the total factor productivity (TFP) of different production days having different network uptime hours show high degree of closeness and this indicates feasibility for single production function. Therefore, the values of simulation outputs such as *traffic (column L)*, *diesel consumption (column H)*, *grid energy (column F)*, and *uptime hour (column I)* shown in Table 8 provide themselves as empirical data for estimation of the production function of the network. Thus, using this empirical data the constant parameters of Cobb-Douglas production function of equation (1) are estimated as $A=0.6711$, $\alpha=0.4143$, $\beta=0.9401$ and $\delta=0.0721$. Now, the production function is as follows-

$$Q= 0.6711 \times K^{0.4143} \times L_1^{0.9401} \times L_2^{0.0721} \qquad R^2= 0.9961 \qquad \dots (7)$$

The regression equations in respect of *Diesel (K)* & *Uptime* (L_2) and *Grid energy* (L_1) & *Uptime* (L_2) are estimated as follows-

$$K = - 85.1 + 0.716\ L_2 \qquad R^2=99.7 \qquad \dots (8)$$

$$L_1 = 766 + 0.678\ L_2 \qquad R^2=98.4 \qquad \dots (9)$$

This study uses INR 0.55 as *cost of network usage per minute.* Table 9 shows the output of the production function and total factor productivity of the network, which have been estimated using equation (7). Table 10 shows the economic growth of the network when the uptime is increased from 55 percent to 100 percent. The above input and output characteristics of the network shown in Table 9 and Table 10 reveal that there is considerable economic growth with the increase in production input however, there is no increase in productivity since there is no involvement of any new engineering or technology which could convert the input resources to desired output efficiently.

6. Conclusion

The basic concept behind this study is to provide a reliable telecom service to the network users. This study considers network reliability as function of network availability. The demand of network reliability is under threat in the local business environment of telecom industry in Manipur. This is because of involvement of heavy cash outlays in producing the desired network reliability in the local context and this has resulted production uncertainty. In this paper, I examine the characteristics of the wireless telecom network and design a model network based on the behavior of the network. In the production function model designed for the wireless network, network traffic is used as output of the production function. This study applies mathematical models of network traffic and energy consumption in designing simulation models for the traffic and other input decision variables such as network uptime and energy consumption. The software developed for simulation is trained to investigate network traffic as a function of input resources such as diesel fuel, grid energy and network uptime. The information obtained from simulation experiments is then used as empirical data for deducing constant parameters of the production function and in estimation of the production function of the wireless network. The result of the cost-benefit analysis supports for meaningful economic growth with the increase in the uptime of the network. This study reveals that certain business problems of telecom are highly influenced by local environment and to address this, the telecom management must try to understand the industry fully within local context and identify business success parameters even on short-term outlook besides its well-structured day-to-day operations. The simulation approach introduced in this paper will help telecom management solve the problem of production uncertainty associated to high production costs.

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