# Stochastic Congestion Management Considering Power System Uncertainties

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**Abstract:** Congestion management in electricity markets is traditionally done using deterministic values of power system parameters considering a fixed network configuration. In this paper, a stochastic programming framework is proposed for congestion management considering the power system uncertainties. The uncertainty sources that are modeled in the proposed stochastic framework consist of contingencies of generating units and branches as well as load forecast errors. The Forced Outage Rate of equipment and the normal distribution function to model load forecast errors are employed in the stochastic programming. Using the roulette wheel mechanism and Monte-Carlo analysis, possible scenarios of power system operating states are generated and a probability is assigned to each scenario. Scenario reduction is adopted as a tradeoff between computation time and solution accuracy. After scenario reduction, stochastic congestion management solution is extracted by aggregation of solutions obtained from feasible scenarios. Congestion management using the proposed stochastic framework provides a more realistic solution compared with the deterministic solution by a reasonable uncertainty cost. Results of testing the proposed stochastic congestion management on the 24-bus reliability test system indicate the efficiency of the proposed framework.

**Keywords:** Electricity market, stochastic congestion management, Monte-Carlo simulation, Roulette wheel mechanism, contingency, load forecast error.

## 1 Introduction

Congestion in a competitive electricity market occurs when the transmission network is unable to accommodate all of the desired transactions due to a violation in the power system operating limits. Especially, in systems having weak connections among different areas, the congestion problem frequently occurs due to overloading or security requirements. Using a congestion management method, the system operator tries to make possible power market transactions.

Usually, there is a spot market for short term electricity transactions. In the sport market, market participants submit their next-day hourly generation or demand bids to the Independent System Operator (ISO). With submitted bids, the ISO clears the market to schedule the powers and determine the Market Clearing Price (MCP) [1]. In case of no congestion, the cleared market remains valid. However, in case of congestion, rescheduling generations and demands is done to relieve congestions, assuming that the system configuration has already been set. Generators participate in the congestion management market by bidding for up and down their production. Also, demands can bid as Demand Side Bidding (DSB) [2] for up and down their loads. While choosing generators or demands for re-dispatching, the least cost option is picked up to minimize total rescheduling cost or to maximize total social benefit. After rescheduling, the network is operated with no violation or congestion. The congestion management is usually done by the ISO using deterministic values of generations, loads, and power system configuration.

However, the power system has a stochastic behavior in practical operations due to uncertainties in the availability of generation, load, and transmission equipment [3]. For generating units, the uncertainties are caused by unplanned outages, equipment failures, protective relaying, economic factors including fuel prices and market prices, reserve availability, reactive power requirements, climactic variables such as

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precipitation and hydro-power availability, and environmental regulations and emissions restrictions. The renewable sources such as wind, photovoltaic, fuel cells, and gas micro turbines will have even more randomness than traditionally generation sources. For transmission system, the uncertainties are caused by line ratings, environmental factors such as ambient temperature and lightning, unplanned outages and equipment failures. For loads, uncertainties are caused by weather-related factors including temperature and precipitation, economic growth, new types of electronically-controlled loads, and variations in load power factors.

Recent major blackouts in North America and Europe [4] have rekindled the security requirements of power systems, which have been regretfully neglected in favor of more financial concerns in recent years. This renewed interest is motivating research also into the congestion management solutions that account for a more complete set of power system security constraints. It is suggested in [5] that power system security analysis methods should evaluate the "credibility" of failures and their "expected" consequences by means of probabilistic methods [6]. Such probabilistic security analysis of power systems however is generally cursed by computational intractability because of the need to evaluate the probabilities and consequences of a very large number of possible failure modes. These drawbacks have led to hybrid deterministic/probabilistic security analysis methods instead of purely probabilistic ones that require the full enumeration of the possible system states [7-9]. In the hybrid methods, the probabilities or the expected consequences of a restricted set of a priori-defined event are used as security metrics instead of considering all the possible failure modes. For example, in structural design, [8] addressed the criticism related to the uncertainty of the failure probabilities and the complicating computational aspects of probabilistic metrics. In the context of power system planning, [9] proposed the use of a deterministic/probabilistic method to evaluate local and system-wide impacts of pre-defined failures of components.

The solution of congestion management could become cumbersome when system uncertainties are considered. Since the ISO uses congestion management signals for future system planning, it is crucial to correctly detect congestion using the real availability of power system components. Consequently, the ISO has to take into account contingencies considering their probability to retain an enough level of security after congestion management using stochastic rather than deterministic power system parameters. Such a network will be able to withstand expected contingencies without losing stability.

Recently, some techniques are presented for congestion management considering voltage security using deterministic parameters [10-12]. Some of them are limited to only the power system DC model, ignoring power system details compared with the more accurate AC model [10, 12]. In [11], a multi-objective model based on the weighting factors is presented to consider voltage stability by maximizing both the social benefit and the distance to the maximum loading point. In [12], a method ensuring the voltage security considering a fixed load growth after congestion management is proposed. On the other hand, some research is done to model uncertainties in the power market. In [13], a methodology is proposed to determine the optimal amount of transmission system usage. In the proposed approach, the maximum flow at each connection is represented as a random variable in order to obtain the distribution probability of the transmission charges as a function of the transmission system usage. In [14], a hybrid stochastic model with discrete and continuous variables is implemented to evaluate the available transfer capacity, where the availability of generators and circuits are considered as random variables and binomial distributions and fluctuations of loads are taken into account as normally distributed variables. In [15], a stochastic model for long-term solution of security-constrained unit commitment is presented. In the model, outages of generation units and transmission lines as well as load forecasting inaccuracies are modeled as scenario trees using Monte-Carlo simulation (MCS). However, based on the knowledge of the authors of this paper, almost no research up to now is presented for congestion management considering the real stochastic nature of power systems [10].

Due to stochastic behavior of power systems such as the outages of generators and branches and uncertainty of system demand, the security of power systems was traditionally handled by the worst outage case. This is a conservative approach which could lead to a very high cost of operating the power system. Furthermore, outages of multiple components may not be considered in this approach, making unable to cover the possible operational states of power systems. In this paper, a new stochastic framework is proposed for congestion management in power markets considering uncertainty of power system components. Forced Outage Rate *(FOR)* is used to model the uncertainty of equipment comprising generators and transmission branches. The *FOR* is defined for an individual component as *(mean down time) / (mean up time + mean down time)*. For instance, *FOR*=2.5% for a generation unit implies that the out of service time of the unit in average will be $0.025\times8760=219$ hours per a year. Also, the normal probability distribution is used to model the load forecast errors. Considering these uncertainty sources, a set of probable scenarios is generated for power market. Each scenario would represent a possible system state which would include outages of system components and a possible system demand. Scenario reduction is adopted in this paper as a tradeoff between computation time and solution accuracy. Using MCS method [16], a weight to each scenario that reflects the possibility of its occurrence is assigned. After solving the optimization problem for the reduced set of scenarios, the results are aggregated to get the expected values of power system parameters. As a result, using the proposed method, the system operator does congestion management considering the most probable uncertainties of power system components.

The contribution of this paper is to present a new framework for congestion management that is able to consider the stochastic behavior of power system parameters. Using the proposed method, the ISO gets more realistic solution for congestion management than the deterministic solution at a reasonable cost. Indeed, the deterministic solution reflects only one of the probable states of a power system. The solution given by the proposed method captures more uncertainty spectrum than the deterministic solution, as shown in section IV. This implies that the proposed stochastic congestion management leads to a more economically realistic solution than the deterministic method.

The remaining parts of the paper are organized as follows. In section two, the stochastic formulation used in this paper to model the uncertainty sources of power system is illustrated. In section three, congestion management considering stochastic variables is introduced. In section four, numerical results of testing the proposed method on a well-known test system are presented and discussed. Section five concludes the paper.

## 2 Stochastic Formulation of Power System Uncertainties

Potential sources of uncertainty that are modeled in the proposed stochastic congestion management formulation include the outage of generating units and transmission equipment as well as load deviation from the forecasted value. In the proposed formulation, the normal distribution function with roulette wheel mechanism is used to model the load forecast error. Also, the outage probability of generators and branches is modeled using their *FOR* values based on the two-state continuous-time Markov chain model [17]. The stochastic programming [18] is used to consider the uncertainty of loads and equipment.

### 2.1 Scenario Generation and Reduction

In the proposed framework, load uncertainty is considered based on the load forecast error. A normal probability distribution function is assumed for the total load of the network. The probability distribution function for an individual load can be determined by its participation in the total load referred to as load distribution factor. A typical probability distribution function of the forecast error of system total load is shown in Fig. 1. The continuous function is discretized as shown in the figure using a few intervals, all of which have the same width of standard deviation ($\sigma$) and are centered on the zero mean. Here, seven intervals are considered as recommended in [17, 19].

On the basis of different levels of load forecast and their probabilities obtained form the probability distribution function, roulette wheel mechanism [20, 21] is implemented to generate scenarios. For this purpose, at first, the probabilities of different load forecast levels are normalized so that their summation becomes equal to unity. Then, the range of [0,1] is occupied by the normalized probabilities as shown in Fig. 2. To create scenarios, random numbers are generated between 0 and 1. Each random number falls into the normalized probability range of a load forecast level in the roulette wheel. This makes that the load forecast level is selected by the roulette wheel mechanism for the respective scenario. As expected, in the stochastic selection process of the roulette wheel, load forecast levels with larger probabilities have more chance to be selected.

Concurrently, MCS is performed to model the uncertainty associated with the outage of power system facilities including generator and transmission equipment using their *FOR* values. One of the advantages of MCS is that the required number of samples for a given accuracy level is independent of system size [15]; this makes it suitable for large scale simulations such as modeling of the power system uncertainty sources. Considering the two-state continuous-time Markov chain model, in each scenario

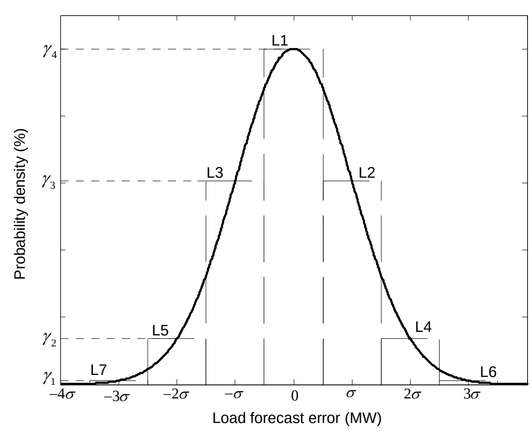


**Fig. 1** Typical probability distribution of the load forecast error and its discretization

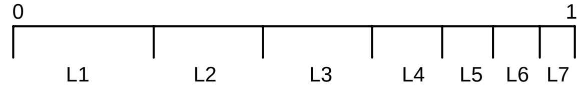


**Fig. 2** The roulette wheel mechanism for the normalized probabilities of the load forecast levels

of the MCS, a random number between [0,1] is separately generated for each generating unit/branch and compared with its *FOR*. If the random number is greater than the equipment's *FOR*, then the equipment is considered in service in this scenario. Otherwise, the equipment is out of service in the scenario. In the proposed stochastic optimization framework, one scenario is constructed by the load level determined from the roulette wheel mechanism along with the status of the generators and branches determined by the MCS. For the problem under study, a given number of scenarios are generated. A higher number of scenarios results in more accurate modeling of uncertainties of course by increasing the cost of computation burden.

Considering the procedure of scenario generation, the probability of each generated scenario is calculated as follows:

$$\pi_s = \sum_{k=1}^{NL}\left(w_{k,s}^{L}.\gamma_k\right).\prod_{e=1}^{Ne}\left(w_{e,s}.\left(1-FOR_e\right)+\left(1-w_{e,s}\right).FOR_e\right) \tag{1}$$

where $w_{k,s}^{L}$ is a binary variable obtained from the roulette wheel mechanism in the scenario generation stage indicating whether $k^{th}$ load level in the $s^{th}$ scenario is triggered (when $w_{k,s}^{L}=1$) or not (when $w_{k,s}^{L}=0$). Also, $\gamma_k$ indicates the probability of $k^{th}$ load level. *NL* and *Ne* indicate the number of load levels and equipment, including generators and branches, respectively. It is worthwhile to note that only one load level, out of *NL* possible levels, is triggered for a scenario; that is $\sum_{k=1}^{NL} w_{k,s}^{L}=1$. According to Fig. 1, *NL*=7. $w_{e,s}$ is the status of equipment *e* in the scenario *s* that is generated by the MCS. Finally, $FOR_e$ and $\pi_s$ are the *FOR* value of equipment *e* and the probability of scenario *s*, respectively.

Computational requirements for solving scenario-based optimization models depend on the number of scenarios. So, an effective scenario reduction technique [22] could be very lucrative for solving large scale models. The reduction technique is a scenario-based approximation with a smaller number of scenarios and a reasonably good approximation of the original system. In the scenario reduction of this paper, first, the identical scenarios are discarded. That is, only one of the similar scenarios with the same load level and with the same status of generators and branches is retained. Second, the scenarios whose probability is very low can be discarded to raise the computational efficiency of the proposed framework. This reduction is adopted in this paper as a tradeoff between computation time and solution accuracy. After generating scenarios and applying the scenario reduction technique, the proposed congestion management, as formulated in the next section, is run for the accepted scenarios. Then, the outputs of congestion management solutions are aggregated to construct expected values of power system parameters.

### 2.2 Aggregation of Solutions

The idea of stochastic programming is to construct or sample possible states of uncertain circumstances, solve the congestion management problem for the possible states, and select a good combination of outcomes to represent the stochastic solution. As stated, the roulette wheel mechanism and MCS method are adapted to simulate random characteristics of power systems and then the scenario aggregation technology is used to solve the stochastic congestion management problem. A major advantage of scenario aggregation technique is that not only individual scenario problems become simple to interpret but also the underlying problem structure is preserved. After running the proposed congestion management for the accepted scenarios resulted from the scenario reduction, the results are aggregated according to the probability of scenarios to get the expected operating point parameters considering uncertainties. The aggregation can be done for solution variables such as generation or demand shifts as well as cost. The aggregation is done as:

$$f = \frac{\sum_{S=1}^{NS}\pi_S \times f_S}{\sum_{S=1}^{NS}\pi_S} \tag{2}$$

where, $f$ is the parameter that is aggregated. Also, $f_S$ and $\pi_S$ are the parameter value at scenario *S* and the probability of scenario *S*, respectively. *NS* is the number of the accepted scenarios after scenario reduction.

## 3 The Proposed Stochastic Congestion Management

The objective function of the proposed congestion management is the cost that the ISO pays to market participants to alter their powers so that congestion is mitigated. The objective function that should be minimized is as:

$$\begin{aligned}\text{Cost} = &\sum_{j\in SG}(B_{Gj}^{up}\Delta P_{Gj}^{up}+B_{Gj}^{down}\Delta P_{Gj}^{down})+\\ &\sum_{k\in SD}(B_{Dk}^{up}\Delta P_{Dk}^{up}+B_{Dk}^{down}\Delta P_{Dk}^{down})+\\ &\sum_{k\in SD}(VOLL_{Dk}\Delta P_{Dk}^{LS})\end{aligned} \tag{3}$$

where, the cost consists of three parts. The two first parts are the payment that the system operator pays to generators and demands to alter their powers as per their bid. The third part is related to the payment of involuntary load shedding that the ISO may apply to loads to manage the congestion in some difficult scenarios. *SG* and *SD* are the set of in service generators and demands, respectively. It is noted that the set *SG* depends on the status of generators in each scenario.

$B_{Gj}^{up}$ and $B_{Gj}^{down}$ are the bid prices of generator $j$ to increase and decrease its power to relieve congestion, respectively. Also, $\Delta P_{Gj}^{up}$ and $\Delta P_{Gj}^{down}$ are up and down generation shifts of unit $j$ that will be determined by the congestion management procedure. Similarly, $B_{Dk}^{up}$, $B_{Dk}^{down}$, $\Delta P_{Dk}^{up}$, and $\Delta P_{Dk}^{down}$ are analogous parameters of demand side bidding. Also, $\Delta P_{Dk}^{LS}$ and $VOLL_{Dk}$ are the amount of involuntary load shedding and the Value Of Lost Load (*VOLL*), respectively. The *VOLL*, paid to demands for the load shedding, depends on the power market policy and is usually much higher than the bids offered by demands to participate in the congestion management market. In the proposed method, load shedding is done when total generation is inadequate to satisfy demands and losses, a phenomenon that may happen in some scenarios with outages of large generation units.

The optimization problem is solved subject to following constraints.

$$P_{Gj}^{\min} \le P_{Gj} \le P_{Gj}^{\max} \tag{4}$$

$$Q_{Gj}^{\min} \le Q_{Gj} \le Q_{Gj}^{\max} \tag{5}$$

$$P_{Dk}^{\min} \le P_{Dk} \le P_{Dk}^{\max} \tag{6}$$

$$0 \le P_{Dk}^{LS} \le P_{Dk}^{\max} \tag{7}$$

$$Q_{Dk} = P_{Dk} \ tan(\phi_{Dk}) \tag{8}$$

$$P_{Gn} - P_{Dn} = |V_n| \sum_{h \in SN} |Y_{n,h}| |V_h| \cos(\delta_n - \delta_h - \theta_{n,h}) \tag{9}$$

$$Q_{Gn} - Q_{Dn} = |V_n| \sum_{h \in SN} |Y_{n,h}| |V_h| \sin(\delta_n - \delta_h - \theta_{n,h}) \tag{10}$$

$$P_{Gn} = \sum_{j \in SGn} P_{Gj} \tag{11}$$

$$Q_{Gn} = \sum_{j \in SGn} Q_{Gj} \tag{12}$$

$$P_{Dn} = \sum_{k \in SDn} P_{Dk} \tag{13}$$

$$Q_{Dn} = \sum_{k \in SDn} Q_{Dk} \tag{14}$$

$$V_n^{\min} \le V_n \le V_n^{\max} \tag{15}$$

$$|S_m(V, \delta)| \le S_m^{\max} \tag{16}$$

$$P_{Gj} = P_{Gj}^{MC} + \Delta P_{Gj}^{up} - \Delta P_{Gj}^{down} \tag{17}$$

$$P_{Dk} = P_{Dk}^{MC} + \Delta P_{Dk}^{up} - \Delta P_{Dk}^{down} \tag{18}$$

$$P_{Dk}^{LS} = P_{Dk} - \Delta P_{Dk}^{LS} \tag{19}$$

$$\Delta P_{Gj}^{up},\ \Delta P_{Gj}^{down},\ \Delta P_{Dk}^{up},\ \Delta P_{Dk}^{down}, \Delta P_{Dk}^{LS} \ge 0 \tag{20}$$

$$j \in SG,\ k \in SD,\ n \in SN,\ m \in SB$$

where, *SN* and *SB* are the set of nodes and in service branches, respectively. Also, *SGn* and *SDn* indicate the set of in service generators and demands connected to bus $n$, respectively. It should be noted that out of service generators and branches in different scenarios are excluded from *SG*, *SB*, and *SGn* sets. Equations (4) and (5) set active and reactive power limits for generators, respectively. These limits are ones that generators would like to declare to the system operator as the permissible range of power for congestion management market and they may not necessarily be the operating limits of machines. Equation (6) sets active power limits offered by demands as the power range for demand side bidding. After rescheduling the demand active power by system operator to relieve congestion, its reactive power is changed according to a constant power factor [12]. Equation (8) adjusts reactive power of demands considering a constant power factor when their active power is rescheduled. AC load flow equations of the power system are represented by Eqs. (9) and (10). Equations (11) and (12) give the total active and reactive generation at buses as the sum of generation units when multiple units are connected to a bus. Similarly, Eqs. (13) and (14) give the total active and reactive load powers at buses when multiple demands present at a bus. Voltage security limits for all buses are set by Eq. (15). The thermal rating of in service branches including lines and transformers is limited by Eq. (16) in terms of apparent power (MVA). In Eq. (17), $P_{Gj}^{MC}$ indicates determined powers by the market clearing procedure before congestion management. Accepted generation shift of generator $j$ in up and down directions in the congestion market, as determined by the proposed method, is given by $\Delta P_{Gj}^{up}$ and $\Delta P_{Gj}^{down}$, respectively. Also, $P_{Gj}$ is the final rescheduled active power of generator $j$ due to congestion management. In Eq. (18), $P_{Dk}^{MC}$ is the demand $k$ stochastic power that is determined by the market clearing procedure according to the roulette wheel and load probability distribution function. $P_{Dk}$ gives demand $k$ rescheduled power to relive congestion only considering demand side bidding. In Eq. (19), $P_{Dk}^{LS}$ gives demand $k$ final rescheduled power after relieving congestion considering the effect of both demand side bidding and involuntary load shedding ($\Delta P_{Dk}^{LS}$). Equation (7) sets the limits of $P_{Dk}^{LS}$. Eq. (20) confines all up and down power changes due to congestion management to positive values.

It is noted that each of the *NS* accepted scenarios has Eq. (3) as the objective function and Eqs. (4)-(20) as the constraints. Only the load level and status of generators and branches are varied in the scenarios. In the proposed stochastic framework, after solving the *NS* congestion management problems, the desired stochastic output variables such as power shifts and cost are aggregated using the obtained solutions of the scenarios based on Eq. (2).

## 4 Numerical Results

The proposed method is examined on the RTS-24 test system, a well-known power system with 24 buses, 32 machines, 33 lines, 5 transformers, and 17 loads. The reason why this test system is selected to examine the proposed method is that standard reliability data such as the *FOR* of equipment are available for this test system. The single line diagram of the system is depicted in Fig. 3 and data of the test system can be obtained from [23]. As an additional assumption in this paper, the rating of branches 3-24, 10-11, 14-16, and 16-17 is set to 200, 150, 300, and 250 MVA, respectively. Also, market data used in the simulations including powers determined by market clearing, lower and upper limits of powers, and bids of generators and demands to participate in the congestion management market are presented in the appendix. *VOLL* is assumed 20 times as much as demand bids to decrease their demand.

All optimizations in this paper are carried out using the CONOPT solver of GAMS 22.7 (General Algebraic Modeling System) software package [24] using its non-linear programming model. It is worthwhile to mention that since generators 22 and 23 are nuclear power plants, they do not participate in congestion management market. Furthermore, generators 24-29, all located at bus 22, are also not participated in the market as they are hydro generators and operate at their maximum output of 50 MW. It is noted that for the sake of simplicity, only uncertainties due to generator and branch outages are considered in the simulations. Indeed, load forecast will be more accurate when the time is getting closer to the market happening time.

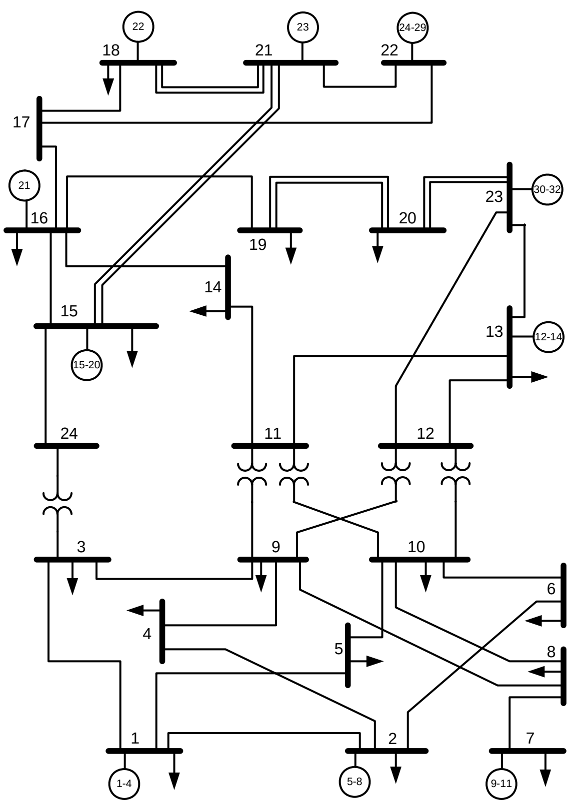

**Fig. 3** One line diagram of the RTS-24 test system

Before applying congestion management, the system is not feasible. In fact, there are some overloaded branches with the generations and loads determined by the market-clearing process. Lines 3-24, 10-11, 14-16, and 16-17 are overloaded to 122.0%, 120.2%, 117.9%, and 142.1% of their rating, respectively. Thus, the system operator has to mitigate the branch overloads keeping system security using a congestion management mechanism.

The congested power market is solved using both the deterministic and stochastic congestion management methods. In the deterministic model, all components of the system are considered in service regardless of their *FOR* value. The rescheduling in generation and demand powers as determined by the deterministic model minimizing the total cost is graphically depicted in Fig. 4.

The cost of congestion relieving by the deterministic model is 4,380.72 \$/h. The ISO pays 1,623.98 \$/h to generators and 2,756.74 \$/h to demands to alter their powers in order to mitigate congestion. Here, the demands are more participated than generators in congestion management.

It is worthwhile to note that the deterministic method assumes fully reliable components of power system and then, the obtained congestion management cost is only valid for fully reliable components with *FOR*=0. Nevertheless, power system components experience some hours of outage annually in practical operations. As a result, the deterministic model can not give a real solution.

To run the proposed stochastic method, a set of 200 scenarios are generated using the *FOR* values of generators and branches. The resulted cases present the probable states of power system. It imposes a high computational burden to solve the congestion

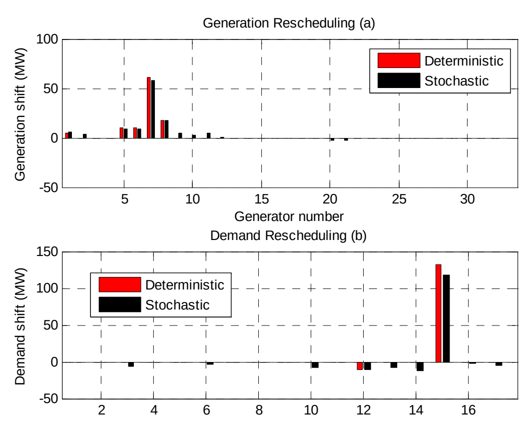


**Fig. 4** Rescheduling of generations (a) and demends (b) as determided by the deterministic and stochastic models

management model for all of these scenarios. So, the set of generated scenarios is reduced using the scenario reduction technique. In the scenario reduction stage, the set is reduced to 132 scenarios after discarding similar ones. After discarding low probable scenarios, the set is more reduced to 20 scenarios. The scenario probability threshold is considered as 0.003; that is, scenarios with the probability less than this threshold are ignored. For the remaining set of scenarios, congestion management is run considering the status of generators and branches in an individual scenario. The results are shown in Table 1.

In Table 1, the number of out of service generators and branches are shown for each scenario. According to the given *FOR* values of generators and branches, the resulting set of scenarios presents the most probable operating states of the power system.

As seen in Table 1, all selected contingencies are single contingencies with the outage of a generation unit or a branch. As expected, according to the well-known probability laws, the occurrence of double and triple contingencies is much less probable. In the next columns, the probability and cost of congestion management is shown for each scenario. In the implemented simulations, congestion in the all scenarios is mitigated without requiring involuntary load shedding. Scenarios with the same probability are resulted from the outage of equipment with the same *FOR* value. As seen in Table 1, in scenario 4, which has the highest probability, neither any generator nor any branch is out of service. Indeed, this scenario represents

**Table 1** Congestion management solutions for the most probable scenarios

| **No.** | **Scenario number** | **Out of service units** | **Out of service branches** | **Probability** ( $\pi_S$ ) | **Cost** ($/h) |
|---|---|---|---|---|---|
| 1 | 4 | --- | --- | 0.143 | 4,380.72 |
| 2 | 7 | --- | 15(9-12) | 0.014 | 5585.78 |
| 3 | 16 | 22 | --- | 0.019 | 7,143.12 |
| 4 | 19 | 12 | --- | 0.008 | 6,119.67 |
| 5 | 21 | 2 | --- | 0.016 | 4,564.27 |
| 6 | 24 | 23 | --- | 0.019 | 7,104.67 |
| 7 | 26 | --- | 16(10-11) | 0.014 | 4,536.70 |
| 8 | 30 | 10 | --- | 0.006 | 5,930.65 |
| 9 | 35 | 32 | --- | 0.012 | 11,459.68 |
| 10 | 49 | --- | 14(9-11) | 0.014 | 6,843.52 |
| 11 | 61 | 1 | --- | 0.016 | 4,564.27 |
| 12 | 65 | --- | 7(3-24) | 0.014 | 11,944.16 |
| 13 | 67 | 6 | --- | 0.016 | 4,567.84 |
| 14 | 69 | 5 | --- | 0.016 | 4,572.84 |
| 15 | 79 | 21 | --- | 0.006 | 7,456.24 |
| 16 | 91 | --- | 17(10-12) | 0.014 | 9,919.86 |
| 17 | 116 | 30 | --- | 0.006 | 7,305.49 |
| 18 | 149 | 9 | --- | 0.006 | 5,940.65 |
| 19 | 194 | 31 | --- | 0.006 | 7,305.49 |
| 20 | 196 | 20 | --- | 0.006 | 5,578.95 |

the non-contingent state of the deterministic case, in which all components are in service. The congestion management cost for this scenario is the same as that of the deterministic model. In fact, according to the obtained results, the probability of this scenario is only 14.3%. This means that the deterministic solution, assuming all components in service, is expected to happen with the low probability of 14.3%. In other words, considering only the non-contingent state, as in the deterministic model, captures 14.3% of the uncertainty spectrum of the power system. Consequently, the deterministic model can not give a proper solution by itself. After the non-contingent case, single contingency states including outage of less reliable equipment (generating unit or branch with higher *FOR* values) are selected as the more probable scenarios.

On the other hand, using the proposed stochastic method, all accepted scenarios contribute into determining the operating point of the power system according to their probability values, whereas the deterministic method relies on scenario 4 as the only contribution to solve the congestion management problem. To relieve congestion, it is expected that the scenario 4 with all components in service requires the least cost generation and demand shifts to satisfy the security requirements. Consequently, this scenario imposes the least cost of congestion management compared to the later contingent scenarios. In other words, the non-contingent scenario has the largest solution space to optimize the congestion management cost shown in Eq. (3). Any deviation from the non-contingent scenario, like the outage of generation units or branches, limits the solution space and at the same time may intensify the congestion problem, which can totally lead to more costly generation or demand shifts and so more congestion management cost.

The aggregated solution in the stochastic model for $\Delta P_{Gj}^{up}$ and $\Delta P_{Gj}^{down}$ is obtained as per Eq. (2) using the accepted scenarios. The results are shown for generations in Table 2 as determined by both deterministic and stochastic solutions. Only nonzero values of power shifts are shown. As seen in Table 2, the dispatch pattern of the stochastic model is different from that of the deterministic model. In order to more precisely study the difference of deterministic and stochastic solutions, the rescheduling of the major different generators in all accepted scenarios is depicted in Fig. 5. The horizontal axis of this figure indicates scenario number (in the range of 1 to 200) and vertical axis represents generation shifts. As seen, all plotted generators have no rescheduling in the non-contingent scenario 4. However, in subsequent contingent scenarios, the congestion management reschedules these generators to satisfy the security constraints of Eqs. (4)-(20) while minimizing the cost of Eq. (3).

To mitigate congestion in the contingent scenarios as seen in Fig. 5, generators 2, 9, and 11 have been the best candidates to increase generation because of the lowest bid and free generation capacity. Furthermore, generators 20 and 21 that are selected to decrease generation have both the best bid and free capacity to decrease power. In view of the fact that the final solution of the proposed stochastic framework is given by the aggregating of scenario results, rescheduling of generators 2, 9, 11, 20 and 21 appear in the stochastic solution of Table 2, whereas there is no need to reschedule these generators in the deterministic solution.

In Table 3, demand shifts determined by the deterministic and stochastic models are also shown. Similar to the generators discussed in Table 2, demands with the best bid and free capacity participate to relieve congestion in the contingent scenarios. This makes differences between rescheduling of the stochastic and deterministic models.

**Table 2** Generation shifts using deterministic and stochastic congestion management

| Gen. | Deterministic $\Delta P_{Gj}^{up}$ (MW) | Deterministic $\Delta P_{Gj}^{down}$ (MW) | Stochastic $\Delta P_{Gj}^{up}$ (MW) | Stochastic $\Delta P_{Gj}^{down}$ (MW) |
|---|---|---|---|---|
| 1 | 4.9 | 0 | 6.1 | 0 |
| 2 | 0 | 0 | 4.2 | 0 |
| 5 | 10.0 | 0 | 8.8 | 0 |
| 6 | 10.0 | 0 | 8.7 | 0 |
| 7 | 60.8 | 0 | 58.5 | 0 |
| 8 | 18.0 | 0 | 17.3 | 0 |
| 9 | 0 | 0 | 4.8 | 0 |
| 10 | 0 | 0 | 2.6 | 0 |
| 11 | 0 | 0 | 5.3 | 0 |
| 12 | 0 | 0 | 0.6 | 0 |
| 20 | 0 | 0 | 0 | 2.2 |
| 21 | 0 | 0 | 0 | 3.1 |

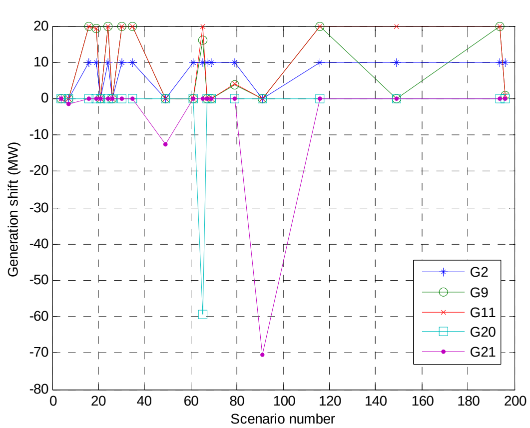


**Fig. 5** The generation rescheduling of the generators whose generations are different in the deterministic and stochatic congestion management

The cost of congestion relieving for generator and demand sides using the deterministic and stochastic methods are separately shown in Table 4.

As seen from Table 4, the ISO pays 4,380.72 $/h to market participants to relieve congestion if the deterministic model is used. According to Table 1, the probability of the deterministic solution is only 14.3%. This means that this scenario has a low probability by itself and the other probable scenarios should be taken into account according to their probability to obtain a more realistic solution. This is done in the proposed stochastic method by aggregating the most probable scenarios. Indeed, the stochastic framework based on the scenario reduction technique tries to capture the uncertainty spectrum as much as possible regarding the computation burden. The cost of the stochastic framework is a bit more than the deterministic one as much as 5,447.92 – 4,380.72 = 1,067.20 $/h. This extra cost is turned up because the contingent scenarios, participated in the aggregated solution, have a congestion management cost greater than the non-contingent scenario. In a fully reliable power system with *FOR*=0, the stochastic and deterministic solutions coincide to a unique solution and this extra cost is zero. By increasing *FOR*, it is expected to increase the extra cost. Then, here we call it the uncertainty cost. Considering the uncertainty cost, we reach the cost of a more realistic congestion management solution. In fact, by paying this fee, the ISO establishes an operating point for the power system considering the possible scenarios of power system configuration, due to unreliable equipment, according to the probability of the scenarios. That is, the system is tolerant of probable

**Table 3** Demand shifts using deterministic and stochastic congestion management

| Dem. | Deterministic $\Delta P_{Dk}^{up}$ (MW) | Deterministic $\Delta P_{Dk}^{down}$ (MW) | Stochastic $\Delta P_{Dk}^{up}$ (MW) | Stochastic $\Delta P_{Dk}^{down}$ (MW) |
|---|---|---|---|---|
| 3 | 0 | 0 | 0 | 7.1 |
| 5 | 0 | 0 | 0 | 1.1 |
| 6 | 0 | 0 | 0 | 3.0 |
| 10 | 0 | 0 | 0 | 7.2 |
| 12 | 0 | 11.2 | 0 | 11.1 |
| 13 | 0 | 0 | 0 | 8.1 |
| 14 | 0 | 0 | 0 | 12.2 |
| 15 | 132.1 | 0 | 117.4 | 0 |
| 16 | 0 | 0 | 0 | 1.8 |
| 17 | 0 | 0 | 0 | 4.3 |

**Table 4** Payment to market participants due to rescheduling given by deterministic and stochastic methods

| | **Deterministic** ($/h) | **Stochastic** ($/h) |
|---|---|---|
| **Generations** | 1,623.98 | 1,999.67 |
| **Demands** | 2,756.74 | 3,448.25 |
| **Total** | 4,380.72 | 5,447.92 |

contingencies under the stochastic solution.

As noted, it is expected to increase the uncertainty cost of the stochastic congestion management solution for less reliable systems including more intensified uncertainty sources. In other words, the solution obtained by the stochastic congestion management depends on the *FOR* values of power system components. To verify this dependency, the stochastic problem of Table 1 is solved with different *FOR* values; the nominal *FOR* values of the test system is multiplied by a coefficient in steps of 0.25. The results are shown in Table 5. In the second column, the probability of the scenario in which all components are in service is reported as all-in-service scenario. The all-in-service scenario indeed reflects the deterministic solution of congestion management. In the next column, the aggregated cost of the stochastic framework for congestion management is shown. In the last column, the uncertainty cost is represented.

As seen from Table 5, the case of *FOR*=0 corresponds to the deterministic solution with only one accepted scenario. In fact, in this case, components of power system are assumed fully reliable. Assuming this *FOR*, solutions of the deterministic and stochastic methods are the same and the uncertainty cost becomes zero. By increasing the *FOR* coefficient, the uncertainty sources are strengthened and the probability of contingencies is increased. This leads to less contribution for the non-contingent scenario and so the probability of the all-in-service scenario is decreased in a less reliable system. This reduction can be seen in column 2. Also, the aggregated cost of stochastic congestion management is increasing because of the fact that the uncertainty in the system increases. As a fact, the uncertainty cost is higher in a less reliable power system. As a result, the deterministic solution, which is used traditionally in congestion management applications, becomes less realistic in less reliable power systems with a high rate of outages. However, the proposed stochastic framework is proper to evaluate the real congestion management for any power system considering its reliability level.

About the validation of results, it is noted that the results that are obtained by the proposed method includes 20 separate scenarios for which the congestion management is solved. Therefore, to validate them, the results as reported in Table 1 should have been validated separately. Nonlinear optimization congestion management for each scenario in Table 1 is solved using the CONOPT solver of the GAMS software package, which is a previously approved optimization tool. As another verification of the results, it can be seen from Table 1 that the congestion management has the least cost for the non-contingent scenario. In a real power market, it is expected to increase the congestion management cost by any outage that causes more limitation on the solution space. This is also seen in Table 1 where the congestion management cost of contingent scenarios is higher than that of the non-contingent scenario. In addition, in a real power system, it is also expected to increase the uncertainty cost by increasing the failure rate of power system equipment. According to Table 5, the uncertainty cost increases with the *FOR* values. This finding can imply another verification of the obtained results in the paper. Finally, it is noted that a new stochastic congestion management framework is proposed in this paper, which presents a more realistic model for the uncertain behavior of the power system equipment. This stochastic framework cannot be directly compared with previous deterministic congestion management models, which underestimate congestion management cost assuming a fully reliable power system.

**Table 5** The effect of *FOR* values on the stochastic solution

| ***FOR* coefficient** | **The probability of all-in-service scenario** (%) | **Aggregated cost of congestion management** ($/h) | **Uncertainty cost** ($/h) |
|---|---|---|---|
| 0 | 100.0 | 4,380.72 | 0 |
| 0.25 | 62.3 | 4,826.48 | 445.76 |
| 0.5 | 38.5 | 5,113.44 | 732.72 |
| 0.75 | 23.6 | 5,329.55 | 948.83 |
| 1.0 | 14.3 | 5,447.92 | 1,067.20 |
| 1.25 | 8.6 | 5,520.04 | 1,139.32 |

## 5 Conclusion

Traditionally, congestion management is performed in power markets using deterministic approaches that consider a fixed configuration for the network as well as the load level forecasted. Nevertheless, nor power system components are fully available neither the forecasted load is completely accurate. In this paper, a stochastic programming framework is proposed to model the power system uncertainties including the outage of generation units and transmission branches as well as load forecast error in the congestion management. The uncertainty of power system components including generators and branches are taken into account using their Forced Outage Rate, while the uncertainty of load forecast is modeled using the normal distribution function. Using the roulette wheel mechanism and Monte-Carlo analysis, possible scenarios of power system operating states are generated and a probability is assigned to each scenario. Scenario reduction is performed to discard unnecessary as well as low probable scenarios in order to increase the computational efficiency of the proposed stochastic programming framework. The proposed congestion management is done for the probable set of scenarios. To obtain a unique solution, the obtained solutions from the acceptable scenarios are aggregated using the probability of each scenario as a weighting factor. The deterministic solution of congestion management provides only one of possible scenarios and then can not reflect the effect of other possible scenarios. However, the availability of power system components and inaccuracies of load forecast are included in the proposed stochastic congestion management method. As a result, the deterministic solution may be somewhat tolerable in systems with high reliability, whereas it can not be realistic in less reliable systems. On the other hand, the proposed stochastic framework can give us a more realistic congestion management solution considering the power system uncertainty sources. Also, the stochastic method can evaluate the extra congestion management cost due to the uncertain behavior of the power system.

## Appendix

Market data of generators and demands used in the simulation are shown in Tables A1 and A2. Also, data of branches including lines and transformers of the test system is shown in Table A3.

**Table A1** Generator data of the test system

| Gen | $P_{Gj}^{MC}$ (MW) | $P_{Gj}^{\min}$ (MW) | $P_{Gj}^{\max}$ (MW) | $B_{Gj}^{up}$ ($/MWh) | $B_{Gj}^{down}$ ($/MWh) | $Q_{Gj}^{\min}$ (MVar) | $Q_{Gj}^{\max}$ (MVar) | $FOR$ |
|---|---|---|---|---|---|---|---|---|
| 1 | 10.0 | 0.0 | 20.0 | 18.00 | 17.00 | 0 | 10 | 0.1 |
| 2 | 10.0 | 0.0 | 20.0 | 18.00 | 17.20 | 0 | 10 | 0.1 |
| 3 | 76.0 | 15.2 | 76.0 | 16.00 | 15.00 | -25 | 30 | 0.02 |
| 4 | 76.0 | 15.2 | 76.0 | 16.00 | 15.50 | -25 | 30 | 0.02 |
| 5 | 10.0 | 0.0 | 20.0 | 17.00 | 16.00 | 0 | 10 | 0.1 |
| 6 | 10.0 | 0.0 | 20.0 | 17.50 | 16.50 | 0 | 10 | 0.1 |
| 7 | 76.0 | 15.2 | 76.0 | 15.00 | 14.00 | -25 | 30 | 0.02 |
| 8 | 76.0 | 15.2 | 76.0 | 15.50 | 14.50 | -25 | 30 | 0.02 |
| 9 | 80.0 | 25.0 | 100.0 | 20.00 | 21.00 | 0 | 60 | 0.04 |
| 10 | 80.0 | 25.0 | 100.0 | 20.50 | 21.50 | 0 | 60 | 0.04 |
| 11 | 80.0 | 25.0 | 100.0 | 20.00 | 21.30 | 0 | 60 | 0.04 |
| 12 | 94.0 | 68.95 | 197.0 | 22.00 | 21.80 | 0 | 80 | 0.05 |
| 13 | 94.0 | 68.95 | 197.0 | 22.50 | 21.50 | 0 | 80 | 0.05 |
| 14 | 94.0 | 68.95 | 197.0 | 23.00 | 22.00 | 0 | 80 | 0.05 |
| 15 | 12.0 | 0.0 | 12.0 | 24.00 | 23.00 | 0 | 6 | 0.02 |
| 16 | 12.0 | 0.0 | 12.0 | 24.50 | 23.50 | 0 | 6 | 0.02 |
| 17 | 12.0 | 0.0 | 12.0 | 25.00 | 24.00 | 0 | 6 | 0.02 |
| 18 | 12.0 | 0.0 | 12.0 | 25.50 | 24.50 | 0 | 6 | 0.02 |
| 19 | 12.0 | 0.0 | 12.0 | 26.00 | 26.50 | 0 | 6 | 0.02 |
| 20 | 155.0 | 54.25 | 155.0 | 19.00 | 20.00 | -50 | 80 | 0.04 |
| 21 | 155.0 | 54.25 | 155.0 | 17.00 | 16.00 | -50 | 80 | 0.04 |
| 22 | 400.0 | 400.0 | 400.0 | 1000.00 | 1000.00 | -50 | 200 | 0.12 |
| 23 | 400.0 | 400.0 | 400.0 | 1000.00 | 1000.00 | -50 | 200 | 0.12 |
| 24 | 50.0 | 50.0 | 50.0 | 16.00 | 15.00 | -10 | 16 | 0.01 |
| 25 | 50.0 | 50.0 | 50.0 | 16.50 | 15.50 | -10 | 16 | 0.01 |
| 26 | 50.0 | 50.0 | 50.0 | 16.00 | 15.20 | -10 | 16 | 0.01 |
| 27 | 50.0 | 50.0 | 50.0 | 16.00 | 15.00 | -10 | 16 | 0.01 |
| 28 | 50.0 | 50.0 | 50.0 | 17.00 | 16.50 | -10 | 16 | 0.01 |
| 29 | 50.0 | 50.0 | 50.0 | 15.00 | 15.40 | -10 | 16 | 0.01 |
| 30 | 155.0 | 54.25 | 155.0 | 24.00 | 25.20 | -50 | 80 | 0.04 |
| 31 | 155.0 | 54.25 | 155.0 | 23.00 | 24.50 | -50 | 80 | 0.04 |
| 32 | 350.0 | 140.0 | 350.0 | 20.00 | 19.00 | -25 | 150 | 0.08 |

**Table A2** Demand market data of the test system

| Demand | $P_{Dk}^{MC}$ (MW) | $P_{Dk}^{\min}$ (MW) | $P_{Dk}^{\max}$ (MW) | $B_{Dk}^{up}$ ($/MWh) | $B_{Dk}^{down}$ ($/MWh) |
|---|---|---|---|---|---|
| 1 | 108.0 | 43.2 | 151.2 | 20.00 | 22.00 |
| 2 | 97.0 | 38.8 | 135.8 | 20.00 | 22.00 |
| 3 | 180.0 | 72.0 | 252.0 | 20.00 | 22.00 |
| 4 | 74.0 | 29.6 | 103.6 | 21.00 | 23.00 |
| 5 | 71.0 | 28.4 | 99.4 | 21.00 | 23.00 |
| 6 | 136.0 | 54.4 | 190.4 | 21.00 | 23.00 |
| 7 | 125.0 | 50.0 | 175.0 | 21.00 | 24.00 |
| 8 | 171.0 | 68.4 | 239.4 | 22.00 | 24.00 |
| 9 | 175.0 | 70.0 | 245.0 | 20.00 | 23.00 |
| 10 | 195.0 | 78.0 | 273.0 | 21.00 | 23.00 |
| 11 | 265.0 | 106.0 | 371.0 | 20.00 | 22.00 |
| 12 | 194.0 | 77.6 | 271.6 | 20.00 | 22.00 |
| 13 | 317.0 | 126.8 | 443.8 | 19.00 | 21.00 |
| 14 | 100.0 | 40.0 | 140.0 | 19.00 | 21.00 |
| 15 | 333.0 | 133.2 | 466.2 | 19.00 | 21.00 |
| 16 | 181.0 | 72.4 | 253.4 | 19.00 | 22.00 |
| 17 | 128.0 | 51.2 | 179.2 | 19.00 | 21.00 |

**Table A3** Branch data of the test system

| **From bus** | **To bus** | **R** (pu) | **X** (pu) | **B** (pu) | ***FOR*** |
|---|---|---|---|---|---|
| 1 | 2 | 0.003 | 0.014 | 0.461 | 0.0018 |
| 1 | 3 | 0.055 | 0.211 | 0.057 | 0.0011 |
| 1 | 5 | 0.022 | 0.085 | 0.023 | 0.0011 |
| 2 | 4 | 0.033 | 0.127 | 0.034 | 0.0011 |
| 2 | 6 | 0.05 | 0.192 | 0.052 | 0.0011 |
| 3 | 9 | 0.031 | 0.119 | 0.032 | 0.0011 |
| 3 | 24 | 0.002 | 0.084 | 0 | 0.0877 |
| 4 | 9 | 0.027 | 0.104 | 0.028 | 0.0011 |
| 5 | 10 | 0.023 | 0.088 | 0.024 | 0.0011 |
| 6 | 10 | 0.014 | 0.061 | 2.459 | 0.0040 |
| 7 | 8 | 0.016 | 0.061 | 0.017 | 0.0011 |
| 8 | 9 | 0.043 | 0.165 | 0.045 | 0.0011 |
| 8 | 10 | 0.043 | 0.165 | 0.045 | 0.0011 |
| 9 | 11 | 0.002 | 0.084 | 0 | 0.0877 |
| 9 | 12 | 0.002 | 0.084 | 0 | 0.0877 |
| 10 | 11 | 0.002 | 0.084 | 0 | 0.0877 |
| 10 | 12 | 0.002 | 0.084 | 0 | 0.0877 |
| 11 | 13 | 0.006 | 0.048 | 0.1 | 0.0013 |
| 11 | 14 | 0.005 | 0.042 | 0.088 | 0.0013 |
| 12 | 13 | 0.006 | 0.048 | 0.1 | 0.0013 |
| 12 | 23 | 0.012 | 0.097 | 0.203 | 0.0013 |
| 13 | 23 | 0.011 | 0.087 | 0.182 | 0.0013 |
| 14 | 16 | 0.005 | 0.059 | 0.082 | 0.0013 |
| 15 | 16 | 0.002 | 0.017 | 0.036 | 0.0013 |
| 15 | 21 | 0.006 | 0.049 | 0.103 | 0.0013 |
| 15 | 21 | 0.006 | 0.049 | 0.103 | 0.0013 |
| 15 | 24 | 0.007 | 0.052 | 0.109 | 0.0013 |
| 16 | 17 | 0.003 | 0.026 | 0.055 | 0.0013 |
| 16 | 19 | 0.003 | 0.023 | 0.049 | 0.0013 |
| 17 | 18 | 0.002 | 0.014 | 0.03 | 0.0013 |
| 17 | 22 | 0.014 | 0.105 | 0.221 | 0.0013 |
| 18 | 21 | 0.003 | 0.026 | 0.055 | 0.0013 |
| 18 | 21 | 0.003 | 0.026 | 0.055 | 0.0013 |
| 19 | 20 | 0.005 | 0.04 | 0.083 | 0.0013 |
| 19 | 20 | 0.005 | 0.04 | 0.083 | 0.0013 |
| 20 | 23 | 0.003 | 0.022 | 0.046 | 0.0013 |
| 20 | 23 | 0.003 | 0.022 | 0.046 | 0.0013 |
| 21 | 22 | 0.009 | 0.068 | 0.142 | 0.0013 |

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