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Realistic Energy Commitments in P2P Transactive Market with Risk Adjusted Prosumer Welfare Trade-off

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Abstract

As the local energy sources are mostly uncertain and fluctuating in nature, the energy risk due to discrepancies between committed transactions and metered measurements is prominent in peer to peer (P2P) markets. To lower the aforementioned risk, this paper proposes an energy risk adjusted welfare maximization problem to trade-off the benefits of buyers and sellers in the P2P market. The risk is modeled using Markowitz portfolio theory and the best point where energy return per unit risk is maximum is obtained from the efficient frontier by using modified Sharpe ratio. The energy portfolio thus obtained is used as a constraint while optimizing the conflicting prosumer benefits using multi-objective stochastic weight trade-off chaotic non-dominated sorting particle swarm optimization (SWTC-NSPSO). In effect, only a reliable proportion of total energy demand submitted in the bid is cleared in the market, foreseeing the real time fluctuations. The proposed market settlement mechanism also gives room to the existing distribution system operators by assigning them the duty of 1) optimally allocating energy among buyers and sellers in accordance with their competitive bids 2) providing the infrastructure, managing the market and charging for the service and 3) checking the technical feasibility by performing load flow and monitoring power transfer sensitivities to encourage short distance transactions. The energy allocation is done in CIGRE LV benchmark microgrid with ten peers having solar and wind generation. The allocated energy is found to be closer to the metered measurements and hence the reserve cost is observed to be low.

Keywords—Peer, energy market, portfolio, risk, multi-objective optimization, PSO

Acronyms

P2P	Peer-to-Peer
DER	Distributed Energy Resources
DSO	Distribution System Operator

SWTC-NSPSO	Stochastic Weight Trade-off Chaotic Non-dominated Sorting Particle Swarm Optimization
BFS	Backward Forward Sweep
SEB	State Electricity Board
MNRE	Ministry of New and Renewable Energy
FiT	Feed-in-Tariff
MCP	Market Clearing Price
UoS	Use of Service charge
RAWM	Risk Adjusted Welfare Maximization
WM	Welfare Maximization
MAPE	Mean Absolute Percentage Error
MAD	Mean Absolute Deviation
RMSE	Root Mean Square Error
PTDF	Power Transfer Distribution Factor

Nomenclature

$\boldsymbol{E_{gi}}, \boldsymbol{E_{di}}$	Generation and demand of i^{th} peer in offer/bid
$\boldsymbol{E_{gi}^{*}}$	Optimal local generation of i^{th} peer
$\boldsymbol{G_{pv}}, \boldsymbol{G_{wind}}$	Total solar and wind generation submitted in the offer/bid
$\boldsymbol{E_{D}}, \boldsymbol{P_{D}}$	Total energy and power demand met during transaction time slot t
$\boldsymbol{n_{d}}$	Total number of peers
$\boldsymbol{E_{k}^{pv}}, \boldsymbol{E_{k}^{w}}$	Energy generation in k^{th} minute from solar and wind respectively
$\boldsymbol{\mu_{pv}}, \boldsymbol{\mu_{w}}$	Average hourly energy generation from solar and wind respectively
$\boldsymbol{\mu_{\Omega}}$	Hourly average energy output from the wind-solar portfolio $\boldsymbol{\Omega}$
$\boldsymbol{\sigma_{\Omega}}$	Standard deviation of energy outputs from the wind-solar portfolio $\boldsymbol{\Omega}$
$\boldsymbol{w_{pv}}, \boldsymbol{w_{w}}$	Proportion of solar and wind generation from the total
$\boldsymbol{w_{pv}^{*}}, \boldsymbol{w_{w}^{*}}$	Optimum weights that maximizes modified Sharpe ratio
$\boldsymbol{E_{s,i}}, \boldsymbol{P_{s,i}}$	Surplus energy and corresponding power transacted by i^{th} seller
$\boldsymbol{E_{b,j}}, \boldsymbol{P_{b,j}}$	Energy and power transacted by j^{th} buyer
$\boldsymbol{S}, \boldsymbol{B}$	Total number of sellers and buyers respectively
$\boldsymbol{MCP_{p2p}}$	Market Clearing Price (MCP) in P2P market
$\boldsymbol{E_{ij}}, \boldsymbol{P_{ij}}$	Committed energy and power transfer between i^{th} seller and j^{th} buyer

$\boldsymbol{UoS_{ij}}$	Use of service charge for energy transfer from i^{th} seller to j^{th} buyer
$\boldsymbol{C}$	Grid power price/tariff
$\boldsymbol{Ploss_{ij}}$	Active power loss due to power transfer from i^{th} seller to j^{th} buyer
$\boldsymbol{Pr_{s,i}}, \boldsymbol{Pr_{b,j}}$	Welfare of i^{th} seller and j^{th} buyer respectively
$\boldsymbol{U_j(E_{b,j})}$	Utility function representing satisfaction level of j^{th} buyer
$\boldsymbol{W_{sellers}}$	Total welfare of sellers
$\boldsymbol{W_{buyers}}$	Total welfare of buyers
$\boldsymbol{P_{grid}}$	Power transacted with grid
$\boldsymbol{P_{loss}}$	Total active power loss in the network
$\boldsymbol{V_{node}}$	Nodal voltage
$\boldsymbol{I_{node}}$	Nodal current injection
$\boldsymbol{S_{node}}$	Nodal complex power injection
$\boldsymbol{N_l}$	Number of distribution lines
$\boldsymbol{P_l}$	Active power flow in line *l*
$\boldsymbol{d_l}$	Utilization charge of line *l*
$\boldsymbol{PTDF_{xy}^{l}}$	Power Transfer Distribution Factor of l^{th} line due to transaction between x^{th} node and y^{th} node
$\boldsymbol{n_{pop}}$	Number of particles generated in SWTC-NSPSO
$\boldsymbol{m}$	Total number of historical minute-wise average generation data
$\boldsymbol{W_u}$	Membership function for u^{th} objective function
$\boldsymbol{W_{obj,u}^{min}}, \boldsymbol{W_{obj,u}^{max}}$	Minimum and maximum values of u^{th} objective function in non-dominated front
$\boldsymbol{W^v}$	Function used for selection of optimum particle
$\boldsymbol{N_{obj}}$	Number of objective functions
nF1	Number of particles in non-dominated front
$\boldsymbol{RM_1}$	Risk index derived from Mean Absolute Percentage Error
$\boldsymbol{RM_2}$	Risk index derived from Mean Absolute Deviation
$\boldsymbol{RM_3}$	Risk index derived from Root Mean Square Error
$\boldsymbol{E_{com}}$	Total local generation committed at time t
$\boldsymbol{E_{avl}}$	Total generation from actual resource available at transaction time t
n	Number of uncertain samples

$\boldsymbol{E_{met,q}}$	Metered generation of q^th^ sample at time t
$\boldsymbol{t_d}$	Duration of energy transaction in hours

1. Introduction

Power networks are under a transition from passive distribution systems to active ones with the penetration of local energy sources. Thus, modern-day consumers have become prosumers by which they satisfy their own demand and with the surplus, they either give back to the grid or deliver to one or more peers. Consequently, local energy trading among peers subscribed to a common market framework is encouraged, leading to a P2P transactive environment [1] - [3]. To facilitate this framework, local energy networks incorporate bidirectional power flow and smart metering, information & communication technology, cyber-physical interaction, decentralized control and trading platforms [4] and [5]. However, these technologies cater to attain different social, environmental and technical objectives based on the extent of liberalization of market in the country of deployment. The review of literature is organized into two groups: 1) Modelling risk and 2) Microgrid prosumer consortium.

Modelling Risk: Regardless of type of the market framework, optimal energy planning is essential in the pre-installation and pre-operational time horizons considering financial and technical risks involved in it. Risks due to different sources of uncertainties are modelled in the literature. Financial risk of the operator due to uncertainties in renewable generation is modelled using affine arithmetic in [6]. The same risk is modelled as the measure of 'profit per unit risk' using Sortino ratio in [7]. However, the authors focused only on the market model 'DSO-Monopoly', where the risk and return were defined in respect of the system operator only. In [8], the effect of fuel price variations on the cash flow risk of GenCo is studied using artificial neural network. Risk in operational cost due to uncertainties in wind speed and dependence of multiple wind farms in economic dispatch problem using mean-variance model is discussed in [9]. In [10], income risk on GenCos due to spot price fluctuations and component failures is modelled using bi-level optimization. Simulation of market behaviour with changing bidding strategies and its effect on GenCo's benefit is modelled using conditional value at risk in [11]. In summary, the aforesaid literature modelled return and risk in terms of financial quantities and were restricted to a single stakeholder. Also, the risk in allocated energy and peer welfare in P2P market due to temporal and spatial variations of renewable energy is unexplored.

Microgrid Prosumer Consortium: Another body of literature focused on a more liberalized market model, the prosumer consortium, where the technical and economic challenges posed by the active distribution networks were addressed by framing a suitable localised market. Several such frameworks including P2P transactions are put forward based on individual and collective welfare, giving rise to new settlement procedure [12], bidding mechanisms [13] and [14], ancillary services market [15], energy management and optimization algorithm [16] etc. However, [12], [13] and [15] did not consider network feasibility, [16] was silent about collective benefits and all of them discarded the conflicting nature of profits. On the other side, there is a moving trend towards decentralized markets with distributed ledger and Blockchain technologies, eliminating the third party for improving security and transparency [17] and [18]. A P2P-ready consensus based distributed algorithm that fully discards the role of the central controller and fully compatible to prosumer preferences, for economic operation of distribution grid is proposed in [19] and [20]. Authors in [17] - [22] viewed the P2P market from prosumers' perspective only, without considering operators' technical preferences. In contrast to the above propositions, some of the recent papers dealt with network constraints also, using sensitivity factors and line flow constraints [23], [24]. Still, an attempt is not made in any of the papers to narrow down the gap between committed and metered energy transactions of peers by modelling risk and return in terms of energy (kWh). In addition, there are contextual challenges with respect to the scale and coverage of deregulation in the country where P2P transactive energy market is envisaged, which is discussed in the following paragraph.

Challenges in Indian Scenario: In a semi-deregulated environment like India [25], [26], the responsibility of meeting the network constraints combined with the enhancement of prosumer benefits should be ideally taken care by the existing operator/third party. In India, the distribution of power at low voltage levels is largely done by state electricity boards (SEBs). However, The Ministry of New and Renewable Energy (MNRE) has proposed various business models where grid-connected solar panels can be either fully owned by a consumer or owned, operated and maintained by the utility. By this, the consumer can feed to grid with his local generation and earn revenue through net metering or renting out his space for PV installations. Still, the consumers lack avenues for local energy trading among neighbors in the present scenario [27], [28]. Hence, the implementation of P2P transactions among the end consumers may not happen all at once, rather the SEBs may be given a different role in the newly designed transactional framework. However, as we move from conventional distribution system to P2P market framework, too many short-term contracts/commitments targeting on individual benefits/welfare would be involved. In such a framework, each market subscriber's sole objective would be to make commitments resulting in maximum profit. As a result, the committed energy transactions will not be in line with the metered measurements in real time. The mismatch is more profound if the relied sources are renewable energy based.

To sum up, when targeting on individual or collective welfare, the contracted volume of energy (typically with renewable energy sources) may be far away from reality and hence the metered measurements would be largely deviating from the committed or cleared energy. Thus, the allocated energy may pose both financial and energy risk to the subscribers/operator based on reserve considerations. An optimal generation mix (different energy technologies in right proportion) that minimizes the energy risk is thus essential for clearing the market depending on the location and time of availability of energy resources. At the same time, conflicting welfares of prosumers should be taken into consideration. In addition, the role of existing operator/owner of the active distribution system cannot be totally discarded from a semi-deregulated viewpoint. Hence, they can serve as a service & infrastructure provider and charge for it based on the network-congestion. Further, the final allocation should be network-feasible and contingent to the competitive bids/offers. In the forerunning context, this paper proposes an energy risk constrained welfare maximized P2P market settlement framework where the main contributions are as follows.

i. Finding the optimal energy portfolio for hourly market clearing using Markowitz mean-variance theory and modified Sharpe ratio which maximises the energy returns and minimizes the energy risk due to lack of firmness in hourly generation. In effect, the risk due to the difference between committed and metered transactions in P2P market is taken care of.

ii. Maximising the conflicting welfares of prosumers (sellers and buyers) using SWTC-NSPSO to determine the peer to peer energy allocation subject to the risk adjusted portfolio obtained in (i). That is, a reliable proportion of energy submitted in the bids/offers is only cleared in the market. The welfare function is designed by considering traded energy, network losses, buyers' comfort level and use of system and service charges.

iii. Checking the network feasibility by conducting backward-forward sweep load flow and thereby calculating the use of service (UoS) charge earned by the third party in accordance with the line flow sensitivities to encourage short distance transactions.

iv. The whole process is carried out in CIGRE LV benchmark microgrid with ten peers having solar/wind generation. The risk adjustment is validated using risk metrics derived from MAPE, MAD and RMSE.

Potential application in Indian context: A local P2P market can be realized in the existing distribution infrastructure with subtle modifications carried out by the SEBs themselves. Keeping them as a third party for managing the market and ensuring the network feasibility, the prosumers/consumers can involve in local energy trading as market subscribers. Before every trading hour, the SEB collects the willingness of subscribers regarding the quantity and price of the energy to be transacted. The SEB then clears the market and arrive at the optimal energy to be allocated among peers considering social welfare maximization, network feasibility checks and energy risk constraints. These services are charged under the UoS component.

The paper is organized as follows. The methodology is given in Section 2. Test system, results and discussions are described in Section 3. The paper is concluded in Section 4.

2. Methodology

The role and responsibility of the third party in conduction of the P2P market is shown in Fig.1. The trading starts with the submission of bids by prosumers which has the information on maximum local generation, load demand, desired selling and buying prices for the time period t. From the bids/offers submitted till time t-1, the third party clears that proportion of load demand which can be met from the optimal solar-wind generation portfolio. Then, energy is allocated among sellers and buyers corresponding to their maximum traded-off welfare, subject to the network constraints, keeping the wind-solar mix intact. In real time, any deviation from the committed energy is met from the grid. The financial settlement for the traded energy is then processed within a month.

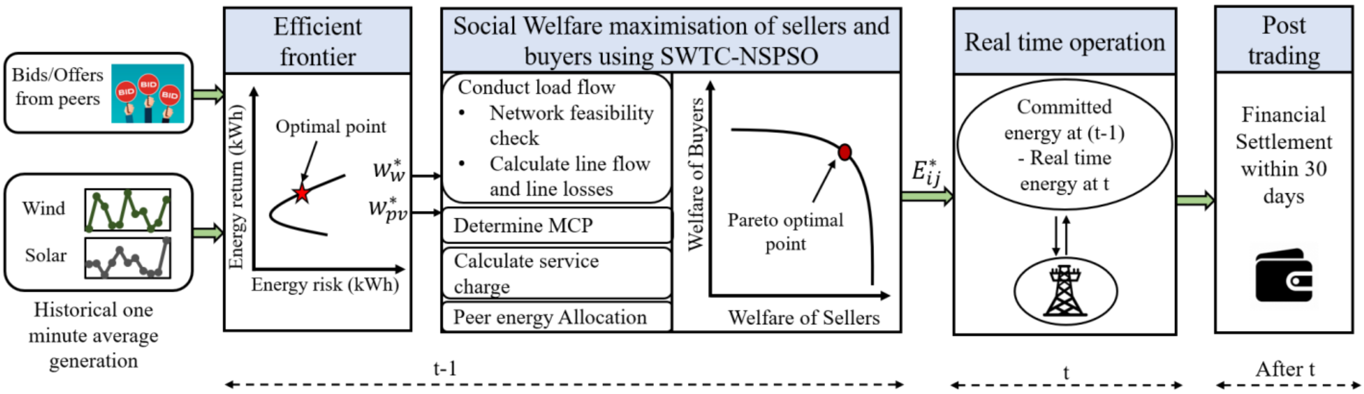

Fig. 1. The proposed P2P market settlement

2.1 Processing bids and optimising energy portfolio

The peers willing to participate in trading hour t are allowed to submit offers/bids till gate closure (an hour prior to the actual trading). Let ($E_{g,i}, E_{d,i}, offer_i/\ bid_i$) be the willingness submitted by the i[th] peer where $E_{g,i}$ and $E_{d,i}$ represent the maximum possible generation and the load demand in kWh during time t. The terms $offer_i$ and bid_i represent the desired selling and buying prices respectively. As the peers are to be lured for P2P trading compared to the conventional (as per the existing monopolistic framework) grid power trade at tariffs/FiTs, the offer is kept higher than feed-in-tariff (FiT) and the bid is lower than the tariff.

Here, the inherent temporal variation of solar and wind generation over an hour is modelled using Markowitz mean-variance theory [28], [29]. Instead of taking financial assets into consideration, wind and solar energy are considered here. Now, the expected value of hourly energy output for various generation mix proportions is calculated to obtain the return of portfolio and the portfolio standard deviation represents the risk. The historical minute-wise average generation of the given sources for the month under consideration is used to model the energy risk and return. E_k^{pv} and E_k^w represent the total energy produced at k[th] minute by the PV and wind sources respectively. The expected hourly generation is then calculated using equations (1) and (2).

$$\mu_{pv} = \frac{1}{m}\sum_{k=1}^{m} E_k^{pv} \tag{1}$$

$$\mu_w = \frac{1}{m}\sum_{k=1}^{m} E_k^{w} \tag{2}$$

$w_{pv}, w_w \in [0,1]$ be the weights of solar and wind generation respectively. The expected hourly energy return from the portfolio is calculated using equation (3) and the portfolio risk (standard deviation) is obtained using equation (4). The matrix Cov represents the covariance between wind and solar generation. The efficient frontier as shown in Fig. 2 is then drawn by varying the weights, satisfying equation (5). For the same energy risk level D in Fig. 2, expected energy return is more for the upper part (point A) compared to the lower part (point B) of the curve. Hence, the upper portion (efficient frontier) of the curve is the searched for the optimal point.

$$\mu_{\Omega} = w_{pv}\mu_{pv} + w_w\mu_w \tag{3}$$

$$\sigma_{\Omega}^2 = [w_{pv} \quad w_w][Cov]\begin{bmatrix} w_{pv} \\ w_w \end{bmatrix} \tag{4}$$

$$w_{pv} + w_w = 1 \tag{5}$$

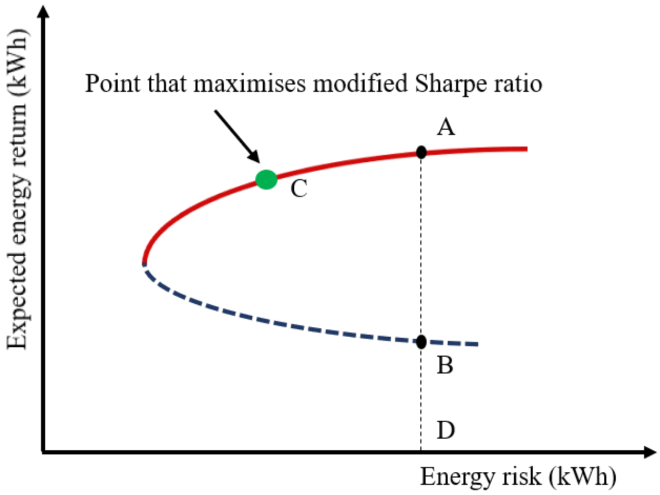

Fig. 2. Efficient frontier

The total load demand submitted in the bid is fully or partially met from the optimal mix of solar-wind generation obtained from the efficient frontier as shown in equation (6). The best point from the efficient frontier is then selected by using the concept of Sharpe ratio. The ratio in finance represents the average excess return earned per unit of total risk [30]. Here, it is modified by replacing the 'excess' financial return by expected energy return (kWh) for the portfolio. The optimal weights are obtained by maximizing the modified Sharpe ratio $\frac{\mu_{\Omega}}{\sigma_{\Omega}}$ using equation (7).

$$\underbrace{(w_{pv} \times G_{pv}) + (w_w \times G_{wind})}_{E_D} \leq \sum_{i=1}^{n_d} E_{di} \tag{6}$$

$$[w_w^* \; w_{pv}^*] = arg\left(max\left\{\frac{\mu_{\Omega}}{\sigma_{\Omega}}\right\}\right) \tag{7}$$

A proportion w_w^* of total energy demand E_D is cleared from wind and w_{pv}^* from solar. These weights serve as energy risk constraints in the P2P market settlement process.

2.2 Peer energy allocation

From the bids and offers submitted by the peers, the power surplus/deficit available for trading is determined and the market-clearing price (MCP) is derived using double auction with average mechanism [21] as shown in equation (8).

$$MCP_{p2p} = \frac{\sum_{i=1}^{S} offer_i + \sum_{j=1}^{B} bid_j}{S + B} \tag{8}$$

Now, the sellers are arranged in the ascending order of their offer prices and the buyers are arranged in the descending order of their bids. Then, energy allocation is done by the market operator, starting from the seller with lowest offer (i=1) and the corresponding buyer with highest bid (j=1), as shown in algorithm-1, satisfying the power balance constraints $E_{s,i} = \sum_{j=1}^{B} E_{ij}$ and $E_{b,j} = \sum_{i=1}^{S} E_{ij}$.

Algorithm 1

Input $E_{s,i}$, $E_{b,j}$

abc: ***for*** *i = 1 to S*

  for *j = 1 to B*

    $E_{ij} = min(E_{s,i}, E_{b,j})$

    $E_{s,i} = E_{s,i} - E_{ij}$

    $E_{b,j} = E_{b,j} - E_{ij}$

    if *(*$E_{s,i} = 0$*) // seller i is cleared*

      goto *abc*

    end if

  end for

end for

2.3 Modeling the welfare of prosumers

The P2P Energy transactions are not assumed to be one-to-one. The welfare of sellers and buyers are modelled as the difference between revenue and expense in equations (9) and (10) respectively. The seller earns revenue from the sale of surplus generation (1st term of equation (9)) and the buyer's revenue is the monetary representation (1st term of equation (10)) of his satisfaction level while consuming power. The response of the buyer for different amounts of power consumption at different time intervals and climatic conditions is modelled as a quadratic utility function satisfying properties related to consumer's choice [21], [31]. For every transaction between ith seller and jth buyer, they should pay UoS charge (2nd term of equations (9) and (10)) to the network owner/third party for utilizing the distribution network and availing the service of managing the P2P market. Also, an additional amount for network losses involved in the transaction is equally shared among buyer and seller (3rd term of equations (9) and (10)). Finally, the 4th term of equation (10) represents the cost of power purchase at MCP.

$$Pr_{s,i} = \left(MCP_{p2p} \times E_{s,i}\right) - \frac{1}{2}\left(\sum_{j=1}^{B} E_{ij} \times UoS_{ij}\right) - \frac{1}{2}\left(\sum_{j=1}^{B} Ploss_{ij} \times C \times t_d\right) \tag{9}$$

$$Pr_{b,j} = U_j\left(E_{bj}\right) - \frac{1}{2}\left(\sum_{i=1}^{S} E_{ij} \times UoS_{ij}\right) - \frac{1}{2}\left(\sum_{i=1}^{S} Ploss_{ij} \times C \times t_d\right) - \left(MCP_{p2p} \times E_{b,j}\right) \tag{10}$$

The objective is to maximise the conflicting welfares (see equation (11)) of buyers and sellers. Hence, the problem is modelled as a multi-objective optimisation problem where the optimum energy allocation trades off the welfare of sellers and buyers (see equations (12) and (13)).

$$max\{W_{sellers}, W_{buyers}\} \tag{11}$$

$$W_{sellers} = \sum_{i=1}^{S} Pr_{s,i} \tag{12}$$

$$W_{buyers} = \sum_{j=1}^{B} Pr_{b,j} \tag{13}$$

2.4 Network feasibility check and calculation of service charge

The network feasibility is checked by performing Backward Forward Sweep (BFS) load flow during the energy allocation process, satisfying the voltage and power balance constraints as shown in equations (14) and (15) respectively. The generation and demand at each node is updated for every updation of allocated energy. The major steps involved are as follows.

1) Input line data and P_{ij}
2) Initialize the bus voltages with 1 p. u.
3) Update power injections at seller node x and buyer node y for every transacted power P_{ij}; +ve for buyer node and -ve for seller node
4) Calculate branch currents from nodal current injections, $I_{node} = \left(\frac{S_{node}}{V_{node}}\right)^*$
5) Update nodal voltages through forward sweep.
6) Repeat steps (4) and (5) until tolerance limit is reached.

$$V_{node}^{min} \leq V_{node} \leq V_{node}^{max} \tag{14}$$

$$w_{pv}^* P_D + w_w^* P_D + P_{grid} = P_D + P_{loss} \tag{15}$$

The use of service charge for a transaction from ith seller to jth buyer is calculated using the Power Transfer Distribution Factor (PTDF) as shown in equation (16).

$$UoS_{ij} = \sum_{l=1}^{N_l} \frac{PTDF_{xy}^l \times d_l}{P_l} \tag{16}$$

Where, d_l and P_l are the utilization charge and the total power flow in the line l, respectively. The term $PTDF_{xy}^l$ represents the change in active power in line *l* due to a transaction from seller node *x* to buyer node y. The $PTDF_{xy}^l$ takes the value zero if the line *l* is not involved in the transaction. For every new energy allocation/transaction, the new line flows corresponding to updated nodal power injections are calculated using BFS load flow.

2.5 SWTC-NSPSO based welfare maximization

The variation of welfare of buyers with respect to optimization of sellers' welfare is shown in Fig.3. As the objectives are found to be conflicting in nature, multi-objective SWTC-NSPSO is used to find the pareto-optimal solution.

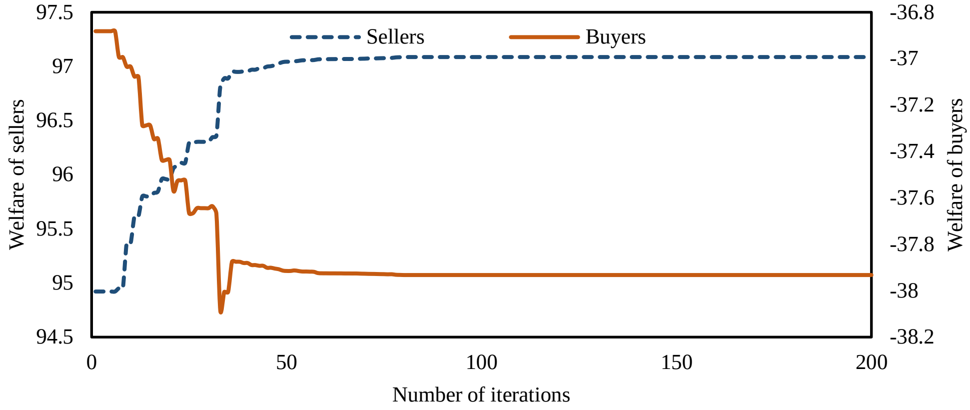

Fig. 3. Variation of welfare of buyers with welfare of sellers

Although the maximum local energy that can be generated is included in the willingness submitted by the peers (E_{gi}), it is updated to the optimal value $E^*_{g,i}$ after maximizing the welfare subject to energy constraints i.e., peer power generation is the decision variable contained in the particle vector. Fig.4. shows energy corresponding to bid/offer values, optimal local generation and the final commitment in the market. $\left(E^*_{gi} - E_{di}\right)$ and $\left(E_{di} - E^*_{gi}\right)$ are the final commitments of seller and buyer in the P2P market respectively.

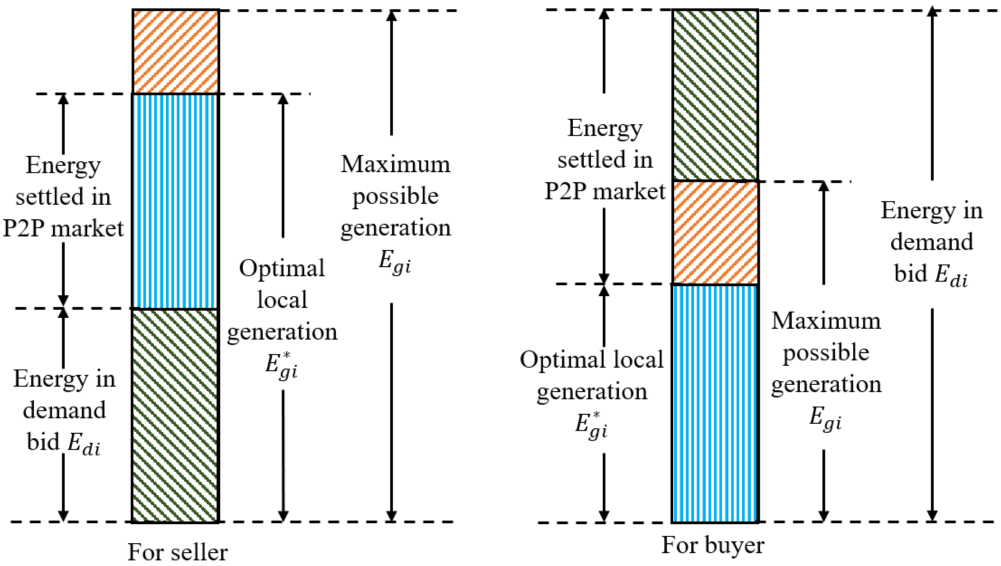

Fig. 4. Energy in bid/offer, optimal local generation and committed transaction in P2P market for seller and buyer

In normal PSO, the velocity and position of the particles are updated to streamline the search for global optimum. Still, there are instances where the solution is trapped in the local optima due to premature convergence and paucity of global best exploration or/and local best utilization. To avoid this, stochastic weight trade-off and chaotic mutation technique involving freak and lethargy factors are incorporated in SWTC-NSPSO [33], [34] by diversifying the search. Also, the swarm members are prioritized in descending order of crowding distance (See Fig. 5) in each iteration to obtain the local best-compromised solutions.

$$\boldsymbol{W_u} = \begin{cases} \boldsymbol{0} & \boldsymbol{W_{obj,u} = W_{obj,u}^{min}} \\ \dfrac{\boldsymbol{W_{obj,u}^{max} - W_{obj,u}}}{\boldsymbol{W_{obj,u}^{max} - W_{obj,u}^{min}}} & \boldsymbol{W_{obj,u}^{min} < W_{obj,u} < W_{obj,u}^{max}} \\ \boldsymbol{1} & \boldsymbol{W_{obj,u} = W_{obj,u}^{max}} \end{cases} \tag{17}$$

$$W^v = \frac{\prod_{u=1}^{N_{obj}} W_u^v}{\sum_{v=1}^{nF1} \sum_{u=1}^{N_{obj}} W_u^v} \tag{18}$$

The normalized variable values of u[th] welfare, W_u ranges from 0 to 1 as the objective value in the pareto front moves from minimum to maximum (See equation (17)). Then, from the pareto optimal front (See Fig. 6) the global best-compromised solution is found from equation (18), which represents the measure of trade-off among welfares 1 and 2. That is, higher the value of W^v, better the solution is.

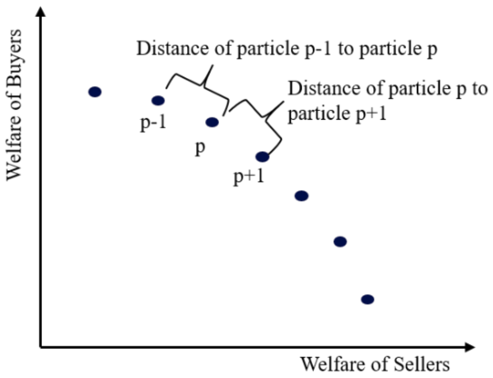

Fig. 5. Crowding distance calculation

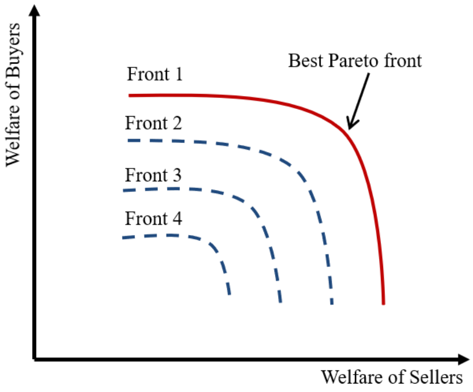

Fig. 6. Non-dominated sorting concept

The major steps involved in the SWTC-NSPSO based welfare optimization algorithm is shown below.

Algorithm 2

Input w_w^*, w_{pv}^*	***For*** *each iteration*
Initialize population with n_{pop} *particles*	***For*** *each particle*
Function *Calculate Welfare*	*Update velocity and position*
Calculate MCP	***End for***
Do energy allocation	***Call:*** *Calculate Welfare*
Perform BFS load flow	*Update pbest and gbest*
Calculate use of system charge	*Merge parent and offspring populations*
Determine welfare of Sellers and Buyers	*Perform non-dominated sorting*
End function	*Select best* n_{pop} *particles*
Initialize pbest	*Plot non-dominated front*
Initialize gbest	***End for***
	Select optimum solution from the front
	Obtain optimum energy allocation E_{ij}^*

2.6 Metrics for validating energy risk

Let E_{avl} be the maximum energy that can be generated during the actual transaction period in accordance with the resource availability. If E_{avl} is greater than or equal to the committed energy generation (E_{com}), then the metered measurement is considered to be equal to E_{com} else, the metered energy is equal to E_{avl}. That is, the scenarios in which E_{avl} is less than E_{com} are considered to be 'risky'. To validate the risk in deviation of metered energy measurements from the committed transactions, the metrics RM_1, RM_2 and RM_3 are used as shown in equations (19), (20) and (21). These indices are derived from Mean Absolute Percentage Error (MAPE), Mean absolute Deviation (MAD) and Root Mean Square Error (RMSE) respectively. Metered measurements are generated from possible uncertainties of wind and solar energy profiles which will add-up to n samples.

$$RM_1 = \frac{100\%}{n} \sum_{q=1}^{n} \left| \frac{E_{com} - E_{met,q}}{E_{com}} \right| \tag{19}$$

$$RM_2 = \frac{1}{n} \sum_{q=1}^{n} \left| E_{com} - E_{met,q} \right| \tag{20}$$

$$RM_3 = \sqrt{\frac{\sum_{q=1}^{n} \left(E_{com} - E_{met,q}\right)^2}{n}} \tag{21}$$

3. Results and Discussion

The modified CIGRE LV network [35] shown in Fig.7. is used as the test system. A total number of 10 peers are assumed in the system where one of them is a consumer and the remaining nine are prosumers with wind or solar generation. The generation and demand of each peer are given in Fig.7.

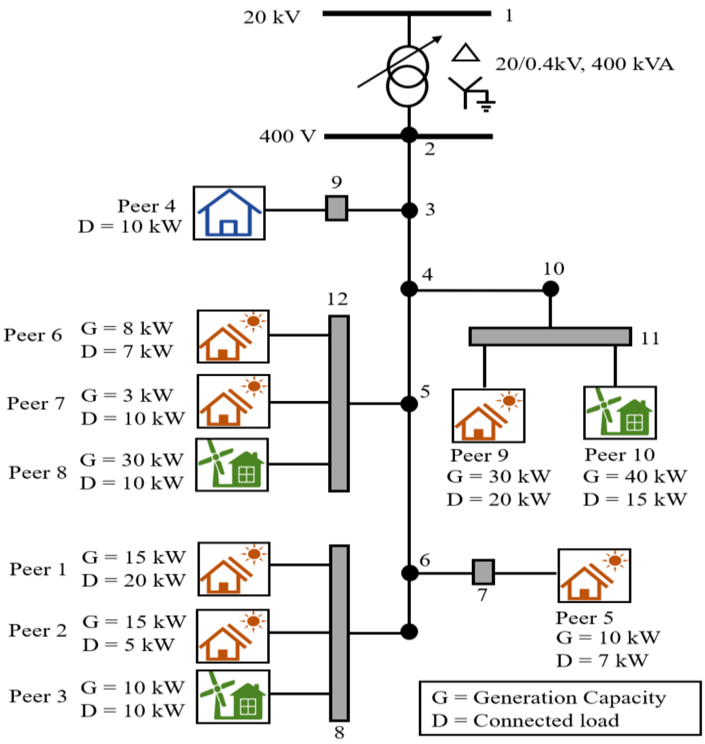

Fig. 7. Modified CIGRE LV system

The hourly load and generation profiles of the system are given in appendices A and B. The time of use tariff and FiTs are shown in Appendix C. The location considered for the study is Cochin, India. Hours 11 to 15 (10:00 AM to 3:00 PM) at which sufficient solar and wind generation is available, is considered for modelling. The maximum possible generation from wind and solar corresponding to the bids (G_{wind} and G_{pv}) and the total demand are shown in Fig.8.

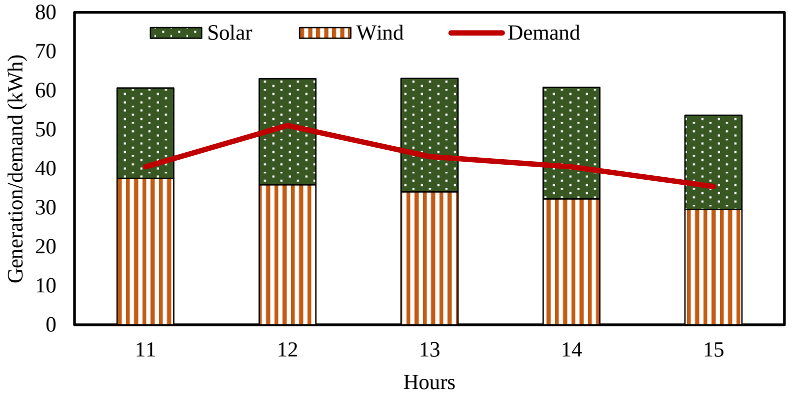

Fig. 8. Maximum possible generation from wind and solar along with load demand

Figures 9 and 10 show the energy return versus energy risk plots for the locations Cochin and Tiruchirappalli in the 15th hour. The points O and O' represent optimum portfolio corresponding to the maximum value of modified Sharpe ratio given in equation (7) subject to the constraint in equation (6). The corresponding optimum weights for solar and wind generation for Cochin are found to be 0.65 and 0.35 respectively, with a Sharpe ratio of 4.27. But, for Tiruchirappalli, the optimum share of solar is 91% whereas the proportion of wind is as meagre as 9% with a Sharpe ratio of 5.18. Also, the length of efficient frontier for Cochin is more, giving the possibility of better mixing of resources against complete dominance of one of them in Tiruchirappalli as shown in Fig. 10. Though there is a reasonable mix of resources in Cochin, the corresponding portfolio energy return for unit risk is found to be lower (based on modified Sharpe ratio). Hence, for locations like Tiruchirappalli, there should be a dominant solar penetration for energy risk adjusted operation. That is, with the right mix of distributed energy resources, we expect more realistic energy commitments from the prosumers adhering to the real time measurements. Henceforth, in this paper, the P2P market studies and settlements are conducted with the data of Cochin only, as it goes better with the generation data given in Fig. 8.

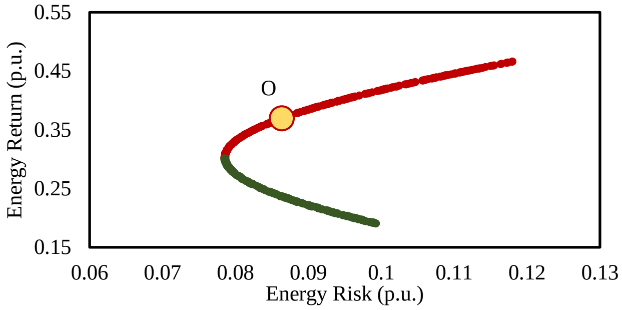

Fig. 9. Efficient frontier for Cochin at 15th hour

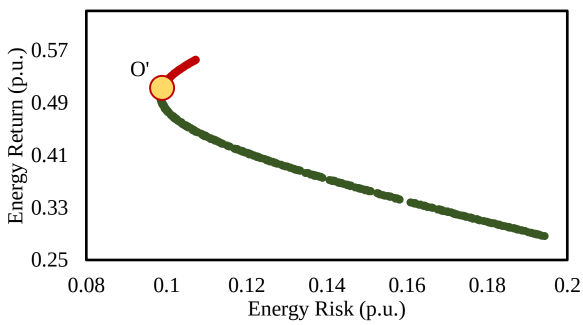

Fig. 10. Efficient frontier for Tiruchirappalli at 15th hour

Table. 1. shows the welfare maximized energy portfolio committed in P2P market with and without risk adjustments. Without risk constraints, the total share of solar and wind energy settled is completely governed by the welfare maximization algorithm. Hence, the riskier wind happens to be more (50% - 57%) weighted than solar (43% - 50%) from welfare point of view. With risk constraints, the proportion of less risky solar is found to be increased.

TABLE. 1. WEIGHTS OF SOLAR AND WIND GENERATION

Hour	Without risk constraint		With risk constraint	
	Weight of solar	Weight of wind	Weight of solar	Weight of wind
11	0.4991	0.5009	0.6869	0.3131
12	0.4896	0.5104	0.6651	0.3349
13	0.4277	0.5723	0.6501	0.3499
14	0.4699	0.5301	0.6278	0.3722
15	0.4736	0.5264	0.6552	0.3448

Figure 11 shows that the total local generation in the system is always less when considering risk. Without risk consideration, the higher amount of total energy settled in the market gives a larger welfare to sellers and lower welfare to buyers as seen from the pareto fronts in Fig. 12. In other words, the welfare of sellers is capped and welfare of buyers is imposed a lower limit by the risk constraint.

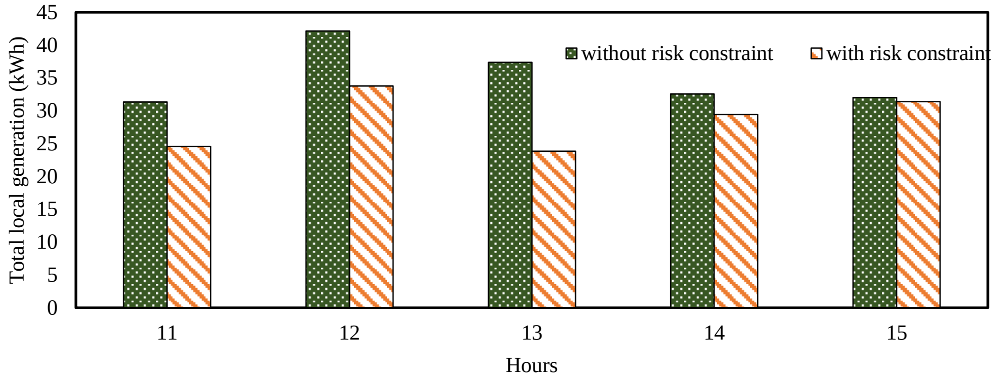

Fig. 11. Total committed generation with and without risk constraint

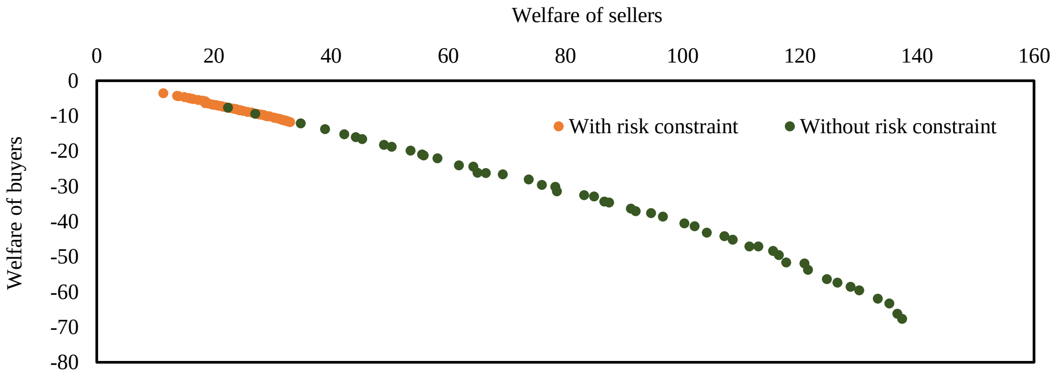

Fig. 12. Pareto fronts with and without risk constraints

The three risk metric values with and without risk consideration is shown in Table. 2. With the incorporation of risk constraint, all the metric values defined in equations (19), (20), (21) have improved significantly. RM_1, RM_2 and RM_3 are reduced by almost 70 percentages when considering energy risk. Consequently, the cost incurred for balancing the deviations is reduced as seen from the lower reserve costs in Fig. 13.

TABLE. 2. COMPARISON OF RISK METRICS

Hour	Without risk constraint			With risk constraint		
	RM_1 (%)	RM_2 (kWh)	RM_3 (kWh)	RM_1 (%)	RM_2 (kWh)	RM_3 (kWh)
11	21.3	6.67	8.05	6.49	1.59	2.34
12	23.59	9.94	11.51	9.32	3.15	3.97
13	22.84	8.54	10.18	8.86	2.11	2.41
14	18.18	5.92	6.87	7.50	2.21	2.72
15	13.02	4.17	5.32	5.71	1.79	2.19

Though the value of RM_2 at 13^{th} hour is higher than that at 11^{th} hour (Table. 2), the reserve cost is more for 11^{th} hour (Fig. 13) because of the higher tariff rate of Rs. 13/kWh against Rs. 7/kWh (See Appendix C).

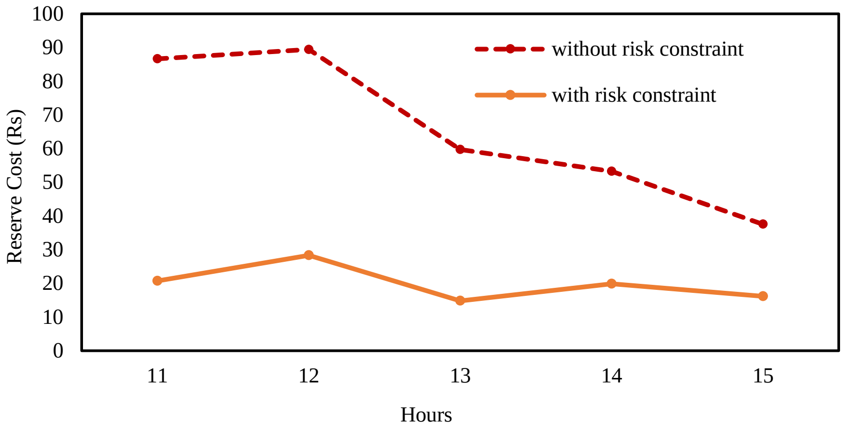

Fig. 13. Reserve cost incurred with and without risk constraints

The peer willingness on expected generation, demand and price is communicated to the third party as shown in Table. 3. This is based on the wind/solar and load profiles shown in appendices A and B. It is evident that peers 1,3,5,6,8 and 10 are sellers and peers 2,4,7 and 9 are buyers during this hour depending on their energy surplus and deficit shown in Fig. 14. Negative energy represents deficit and positive energy amounts to surplus. Now, based on simple welfare maximization (WM) or energy risk adjusted welfare maximization (RAWM), the final allocated energy would be a proportion of this surplus/deficit. However, a lower proportion is obtained from RAWM.

TABLE. 3. INPUT FROM PEERS FOR 13TH HOUR

Peers	Generation (kWh)	Demand (kWh)	Offer Price (Rs/kWh)	Bid Price (Rs/kWh)
Peer 1	7.652	1.729	2.17	-
Peer 2	1.913	6.498	-	6.96
Peer 3	4.254	3.282	2.29	-
Peer 4	-	2.831	-	6.27
Peer 5	3.826	1.469	3.76	-
Peer 6	3.061	2.448	2.11	-
Peer 7	1.148	5.822	-	6.88
Peer 8	12.763	1.635	2.83	-
Peer 9	11.479	14.887	-	5.02
Peer 10	17.017	2.453	3.68	-

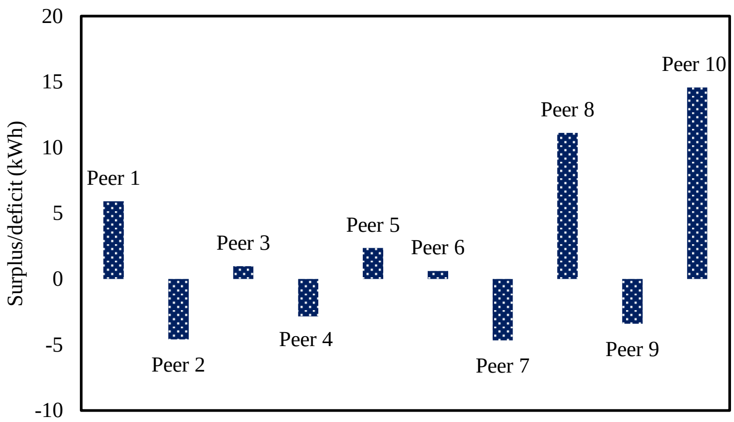

Fig. 14. Surplus/deficit energy of peers

The market clearing price is calculated from the submitted offers/bids as Rs 4.2/kWh using equation (8). The P2P optimal energy allocation among sellers and buyers in the 13th hour under WM and RAWM is shown in Table. 4. Peer-5 who submitted the highest offer is discarded in WM and peers 4 and 9 with lowest bids are discarded in RAWM based on the energy allocation algorithm given in Section 2.2. Difference is seen in the commitments among peers in accordance with the type of source owned as well. It is seen from Fig. 15 that the shares of peers 1 and 5 with less risky PV dominate in RAWM whereas peers 8 and 10 with riskier wind dominate in WM. Also, the total energy cleared in P2P market is less in RAWM compared to WM, ensuring minimum deviation between committed and metered transactions. That is, a proportion of total generation is only reliable with respect to actual availability of resources. For example, in Fig. 16, the willingness submitted by peer-10 (wind powered) is 17.01

kWh (his expectation) but his local generation is 8.43 kWh after WM whereas it is 2.64 kWh after RAWM. Finally, the energy committed in P2P market after meeting his own load is only 200Wh with RAWM. Obviously, a portion of energy from the wind-based peer would be shifted to PV-based peers (1 & 5) with RAWM as shown in Fig. 15.

TABLE.4. PEER TO ENERGY ALLOCATION WITHOUT RISK CONSTRAINT

Sellers \ Buyers		Peer 2	Peer 7	Peer 4	Peer 9
Peer 6	RAWM	0.1284			
	WM	0.3841			
Peer 1	RAWM	4.5998	0.7968	-	-
	WM	2.7767			
Peer 3	RAWM	-	0.4911	-	-
	WM	0.4250			
Peer 8	RAWM	-	0.2947	-	-
	WM	2.3127	5.3052		
Peer 10	RAWM	-	0.1911	-	-
	WM		0.2094	2.8313	2.9362
Peer 5	RAWM	-	1.9639	-	-
	WM				

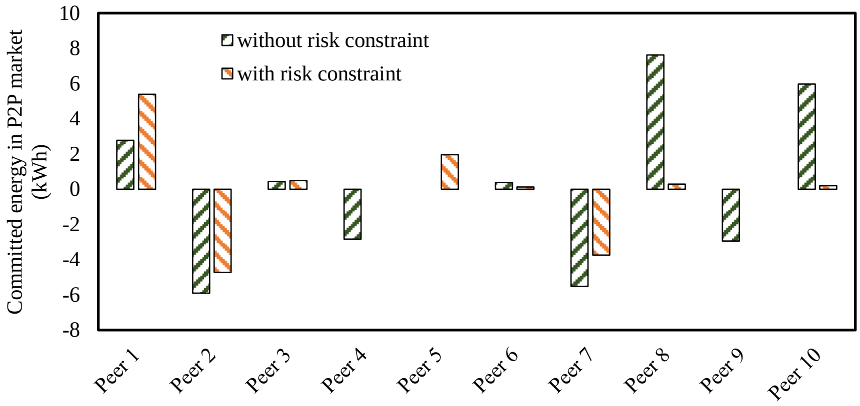

Fig. 15. Committed P2P transactions with and without risk constraint

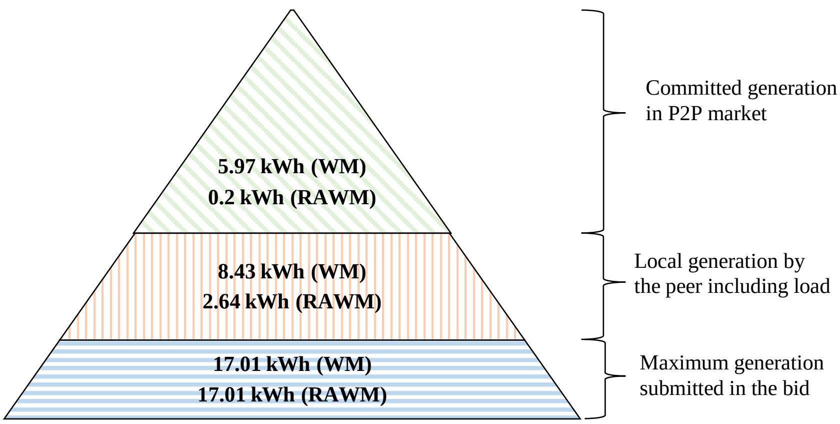

Fig. 16. Energy in offer, optimal local generation and commitment in P2P market of peer-10.

Figures 17 and 18 depict the change in welfare and energy of peers with and without risk consideration. The contribution of welfare from wind-based peers (3, 8 and 10) is found to be 81% under WM but its share is drastically dipped to 10% under RAWM. This is compensated by the welfare of solar-based peers (1 and 5) by about 70%. The corresponding shift in energy is evident from Fig. 18 (red color represents solar energy and green represents wind). The shares of total local generation after trading-off the welfare is shown in Fig.18. Peers 4 and 9 are discarded in RAWM where the total energy cleared is less because their incompetent bids couldn't find suitable sellers. With RAWM, the updated energy cap for total wind generation has affected the welfares of peers 8 and 10 compared to peer-3 (See Fig. 17) because of the competent offer price submitted by peer-3 (See Table. 3).

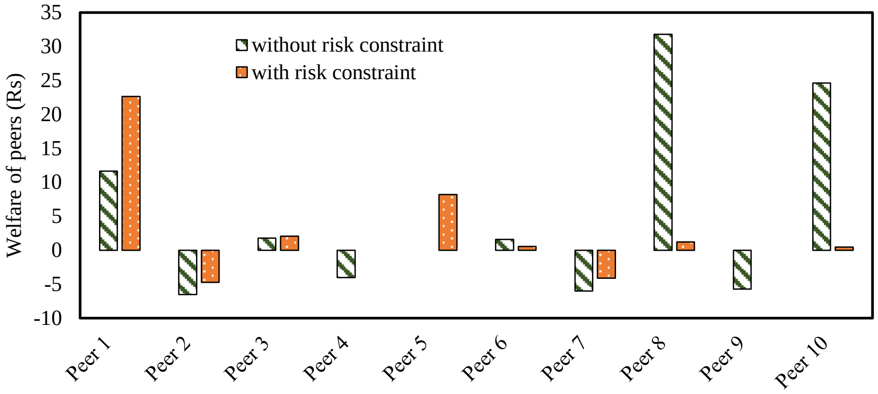

Fig. 17. Welfare of peers with and without risk constraint

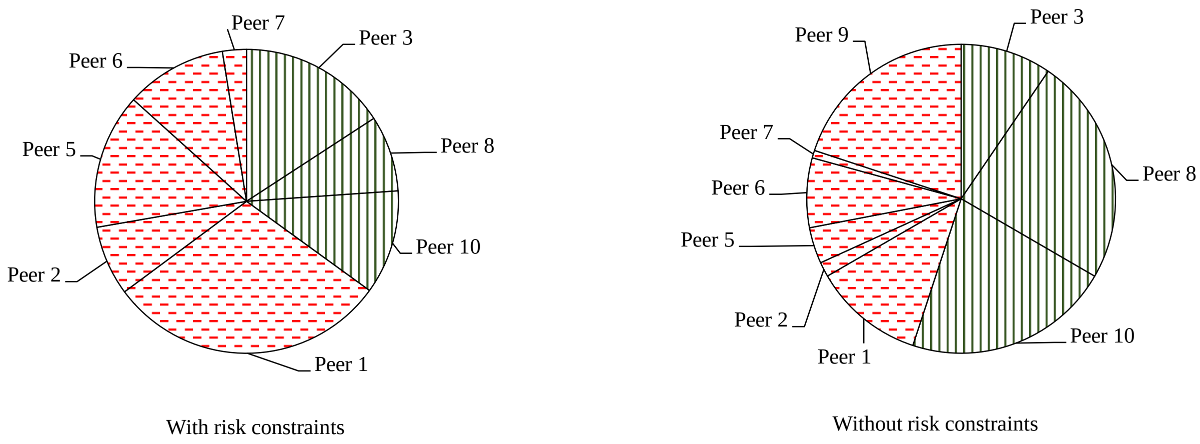

Fig. 18. Local generation from peers in WM and RAWM

The comparison of nodal voltage profiles when the same amount of energy is cleared through P2P as well as from the main grid (without local generation) is shown in Fig. 19. In general, the voltage profile is almost nominal because of enough local generation in the system under P2P settlement. For example, the voltage of farthest node 8 is 0.97 p.u. when fed from the grid whereas it is improved to 0.998 p.u. with P2P settlement. With P2P transactions, peer-2 buys 54% of its energy from peers 2 and 3 located at the same node-8 and remaining from the nearby node-12.

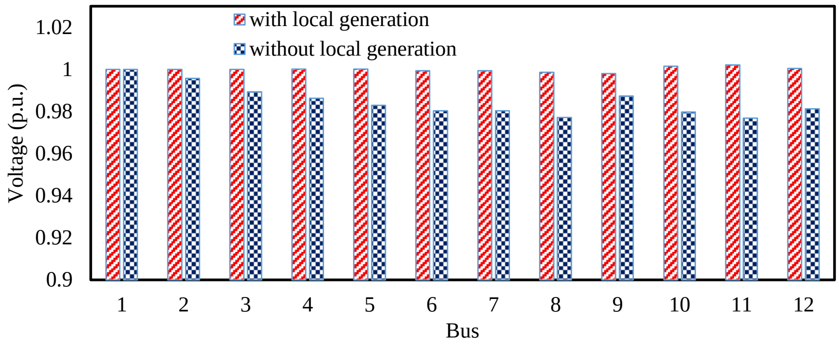

Fig. 19. Nodal voltage profiles with and without local generation

The non-dominated pareto fronts obtained after welfare maximization using SWTC-NSPSO are shown in Fig. 20. It is evident that the pareto front under RAWM is much smaller compared to WM due to lower amount of cleared energy. The global compromised solution shown in the figure is obtained from the criteria given in equations (17) and (18).

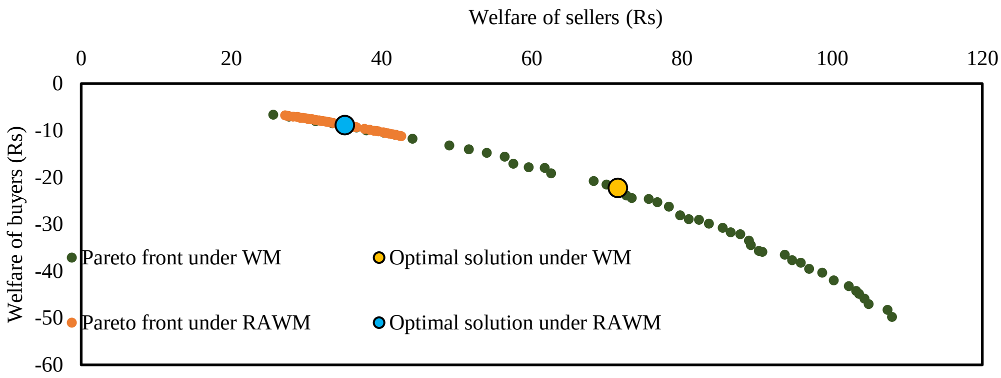

Fig. 20. Pareto fronts obtained after welfare maximization under WM and RAWM

4. Conclusion

An energy risk adjusted welfare maximization problem is formulated to obtain more realistic energy commitments from prosumers in the P2P market. The risk model is derived from Markowitz mean-variance portfolio theory and Sharpe ratio. The committed energy in P2P market is found to be closer to metered measurements based on the defined risk measures derived from mean absolute percentage error and deviation. Consequently, the reserve cost is found to be lower with risk adjusted commitments. Also, the conflicting welfares of sellers and buyers are found to be traded-off, subjected to risk and network feasibility constraints, by using SWTC-NSPSO and backward-forward sweep load flow. The optimal peer energy allocation thus obtained is in line with the competence of bid/offer prices submitted, prescribed voltage limits, nature of risk involved in type of source owned and location of the peer in the network. Further, the service of market conduction and network utilization is charged by the third party based on power transfer sensitivities and total energy cleared. Although the total energy cleared in the P2P market is found to be less with risk adjustments, the energy return per unit risk is found higher. The model also recommends having an optimal mix of energy sources in the distribution system to facilitate clear-sighted conduction of P2P market.

Appendix A – 24-hour wind and solar generation profile

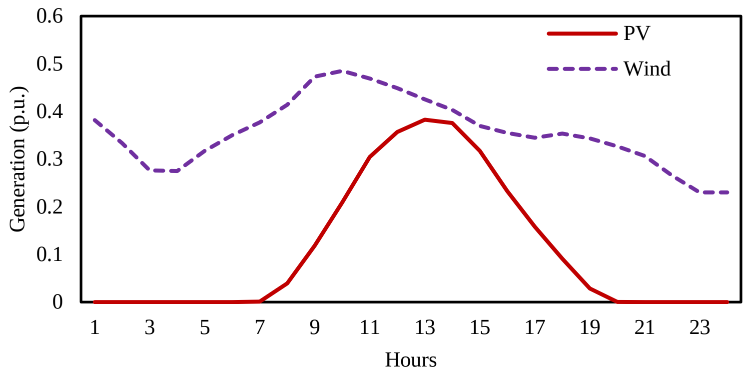

Fig. A.1. Sample solar and wind generation profile of a day

Appendix B – 24-hour load demand profile

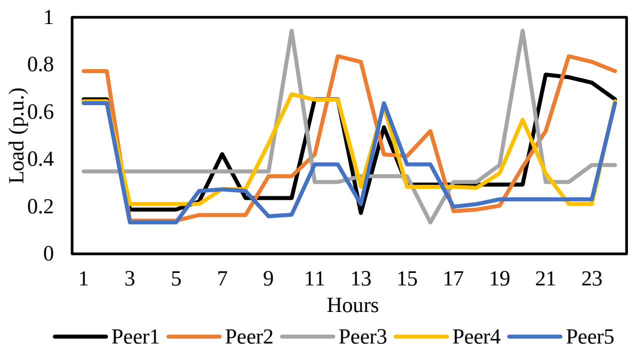

Fig. B.1. Load profiles for peers 1 to 5

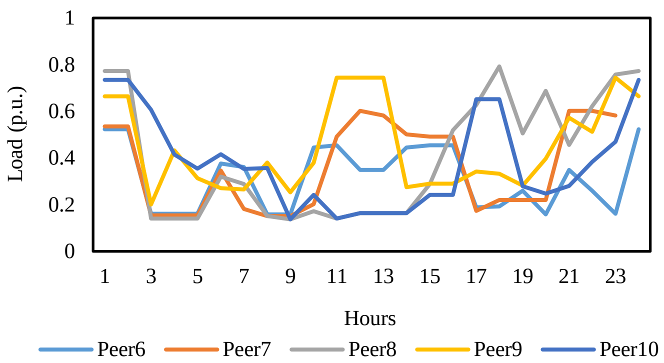

Fig. B.2. Load profiles for peers 6 to 10

Appendix C - Tariff and FiT rates

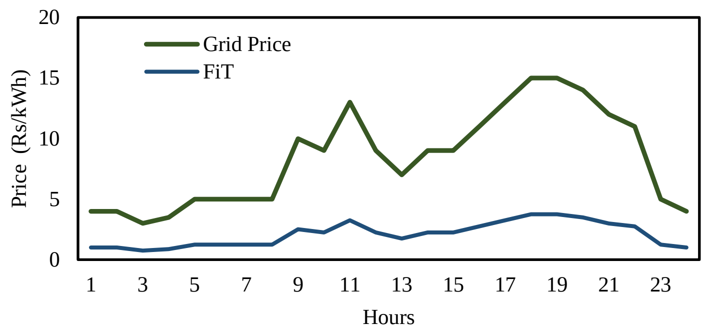

Fig.C.1. 24-hour grid power price and FiT rates

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REFERENCES

[1] Y. Parag and B. K. Sovacool, "Electricity market design for the prosumer era," *Nature Energy*, vol. 1, March 2016.

[2] M.Khorasany, Y.Mishra and G.Ledwich, "Market Framework for Local Energy Trading: A Review of Potential Designs and Market Clearing Approaches", *IET Generation Transmission & Distribution,*2018.

[3] C. Zhang, J. Wu, Y. Zhou, M. Cheng, and C. Long, "Peer-to-Peer energy trading in a Microgrid", *Applied Energy,* vol. 220, pp. 1-12, 15 June 2018.

[4] B. Yildiz, J.I. Bilbao, J. Dore, A.B. Sproul, "Recent advances in the analysis of residential electricity consumption and applications of smart meter data", Applied Energy,Volume 208,2017,Pages 402-427,ISSN 0306-2619,https://doi.org/10.1016/j.apenergy.2017.10.014.

[5] Jeremy Every, Li Li, David G. Dorrell, "Leveraging smart meter data for economic optimization of residential photovoltaics under existing tariff structures and incentive schemes" ,Applied Energy,Volume 201,2017,Pages 158-173,ISSN 0306-2619,https://doi.org/10.1016/j.apenergy.2017.05.021.

[6] Vivek Mohan, Jai Govind Singh, Weerakorn Ongsakul, "An efficient two stage stochastic optimal energy and reserve management in a microgrid", *Applied Energy*, Volume 160, 2015, Pages 28-38, ISSN 0306-2619, https://doi.org/10.1016/j.apenergy.2015.09.039.

[7] Mohan, Vivek & Singh, Jai Govind & Ongsakul, Weerakorn, "Sortino Ratio Based Portfolio Optimization Considering EVs and Renewable Energy in Microgrid Power Market", *IEEE Transactions on Sustainable Energy*, 2016. doi: 10.1109/TSTE.2016.2593713.

[8] David C. Rode, Paul S. Fischbeck, "Reduced-form models for power market risk analysis", Applied Energy, Volume 228, 2018, Pages 1640-1655,ISSN 0306-2619, https://doi.org/10.1016/j.apenergy.2018.07.044.

[9] M.S. Li, Z.J. Lin, T.Y. Ji, Q.H. Wu, "Risk constrained stochastic economic dispatch considering dependence of multiple wind farms using pair-copula", Applied Energy, Volume 226, 2018, Pages 967-978, ISSN 0306-2619, https://doi.org/10.1016/j.apenergy.2018.05.128.

[10] Nan Shang, Chengjin Ye, Yi Ding, Teng Tu, Baofeng Huo, "Risk-based optimal power portfolio methodology for generation companies considering cross-region generation right trade", Applied Energy, Volume 254, 2019, 113511, ISSN 0306-2619, https://doi.org/10.1016/j.apenergy.2019.113511.

[11] Hongye Guo, Qixin Chen, Qing Xia, Chongqing Kang, "Electricity wholesale market equilibrium analysis integrating individual risk-averse features of generation companies", Applied Energy, Volume 252, 2019, 113443, ISSN 0306-2619, https://doi.org/10.1016/j.apenergy.2019.113443.

[12] Shantanu Chakraborty, Tim Baarslag, Michael Kaisers, "Automated peer-to-peer negotiation for energy contract settlements in residential cooperatives", *Applied Energy*, Volume 259, 2020, 114173, ISSN 0306-2619, https://doi.org/10.1016/j.apenergy.2019.114173.

[13] Chenghua Zhang, Jianzhong Wu, Meng Cheng, Yue Zhou, Chao Long, "A Bidding System for Peer-to-Peer Energy Trading in a Grid-connected Microgrid", *Energy Procedia*, Volume 103, 2016, Pages 147-152, ISSN 1876-6102, https://doi.org/10.1016/j.egypro.2016.11.264.

[14] Kaixuan Chen, Jin Lin, Yonghua Song, "Trading strategy optimization for a prosumer in continuous double auction-based peer-to-peer market: A prediction-integration model", *Applied Energy*, Volume 242, 2019, Pages 1121-1133, ISSN 0306-2619, https://doi.org/10.1016/j.apenergy.2019.03.094.

[15] G. De Zotti, S. A. Pourmousavi, H. Madsen and N. Kjølstad Poulsen, "Ancillary Services 4.0: A Top-to-Bottom Control-Based Approach for Solving Ancillary Services Problems in Smart Grids," in *IEEE Access*, vol. 6, pp. 11694-11706, 2018.

[16] Nand K. Meena, Jin Yang, Evan Zacharis, "Optimisation framework for the design and operation of open-market urban and remote community microgrids", Applied Energy, Volume 252, 2019, 113399, ISSN 0306-2619, https://doi.org/10.1016/j.apenergy.2019.113399.

[17] E. Mengelkamp, J. Gärttner, K. Rock, S. Kessler, L. Orsini, and C.Weinhardt, "Designing microgrid energy markets: A case study: The Brooklyn Microgrid," *Applied Energy,* vol. 210, pp.870-880, 2018.

[18] M. Andoni, V. Robu, D. Flynn, S. Abram, D. Geach, D. Jenkins, *et al.* "Blockchain technology in the energy sector: A systematic review of challenges and opportunities" *Renew Sustain Energy Rev* ,2019.

[19] H. Pourbabak, Tao Chen and W. Su, "Consensus-based distributed control for economic operation of distribution grid with multiple consumers and prosumers," *IEEE Power and Energy Society General Meeting (PESGM)*, Boston, MA, pp. 1-5. 2016,

[20] T. Morstyn and M. D. McCulloch, "Multiclass Energy Management for Peer-to-Peer Energy Trading Driven by Prosumer Preferences," in *IEEE Transactions on Power Systems*, vol. 34, no. 5, pp. 4005-4014, Sept. 2019.

[21] A. Paudel, K. Chaudhari, C. Long and H. B. Gooi, "Peer-to-Peer Energy Trading in a Prosumer-Based Community Microgrid: A Game-Theoretic Model," in *IEEE Transactions on Industrial Electronics*, vol. 66, no. 8, pp. 6087-6097, Aug. 2019.

[22] W. Tushar, T. K. Saha, C. Yuen, P. Liddell, R. Bean and H. V. Poor, "Peer-to-Peer Energy Trading with Sustainable User Participation: A Game Theoretic Approach," in *IEEE Access*, vol. 6, pp. 62932-62943, 2018.

[23] Khorasany Mohsen & Mishra Yateendra & Ledwich Gerard, "A Decentralised Bilateral Energy Trading System for Peer-to-Peer Electricity Markets," *IEEE Transactions on Industrial Electronics,* 2019.

[24] M. Khorasany, Y. Mishra, and G. Ledwich, "Auction Based Energy Trading in Transactive Energy Market with Active Participation of Prosumers and Consumers," *In Proc. Australian Universities Power Engineering Conf. (AUPEC)*, Melbourne, pp.1-6, 2017

[25] P. Bajpai and S. N. Singh, "An electric power trading model for Indian electricity market," *2006 IEEE Power Engineering Society General Meeting*, Montreal, Que.,2006.

[26] Kumar, S. & Bhattacharyya, Biplab & Gupta, Vikash, "Present and Future Energy Scenario in India," J*ournal of The Institution of Engineers, India ,2014*.

[27] Tamilnadu Solar Energy Policy 2019. [online]. Available at http://teda.in/wp-content/uploads/2019/02/SOLARPOLICY2019.pdf

[28] Grid Connected Rooftop Solar Power Projects under Ministry of New and Renewable Energy, Government of India. [online]. Available at https://mnre.gov.in/solar-rooftop-grid-connected

[29] H. Markowitz, "Portfolio selection," *The Journal of Finance*, Vol. 7, No. 1, pp. 77-91, (1952)

[30] West G, "An Introduction to Modern Portfolio Theory: Markowitz, CAP-M, APT and Black-Litterman," Financial Modelling Agency, 2006.

[31] Sharpe William F, "The Sharpe Ratio," *The Journal of Portfolio Management* ,1994.

[32] B. Chai, J. Chen, Z. Yang and Y. Zhang, "Demand Response Management with Multiple Utility Companies: A Two-Level Game Approach," in *IEEE Transactions on Smart Grid*, vol. 5, no. 2, pp. 722-731, March 2014.

[33] E. Bompard, E. Carpaneto, G. Chicco, and R. Napoli, "Convergence of the backward/forward sweep method for the load-flow analysis of radial distribution systems," *Int. J. Electr. Power Energy Syst.*, vol. 22, no. 7, pp. 521–530, Oct. 2000

[34] A. Man-Im, W. Ongsakul, J. G. Singh and C. Boonchuay, "Multi-objective optimal power flow using stochastic weight trade-off chaotic NSPSO," *2015 IEEE Innovative Smart Grid Technologies - Asia (ISGT ASIA)*, Bangkok, 2015, pp. 1-8.

[35] Man-Im, Anongpun & Ongsakul, Weerakorn & Singh, Jai Govind & Boonchuay, Chanwit, "Multi-objective Economic Dispatch Considering Wind Power Penetration Using Stochastic Weight Trade-off Chaotic NSPSO," *Electric Power Components and Systems*.,2017

[36] Papathanassiou S, Hatziargyriou N, Strunz K. "A benchmark low voltage microgrid network", *CIGRE Symp Power Syst with dispersed Gener Technol impact Dev Oper performances*, Athens, Greece; 2005. p. 1–8.