

Distributed Optimization and Machine Learning

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Lecture 33: Algorithm for Uncapacitated EDP

So, essentially, we need to ensure two things, we need to ensure that there is consensus on lambda, there is consensus on lambda, because this particular lambda is going to be shared between different generators. generators have the dispatch value is going to be this particular quantity right. So, we are going to be ensuring these two things and this basically gives us our algorithm and we are going to then look at the proof of the algorithm to show that this algorithm indeed converges in a fixed time ok. So, algorithm for uncapacitated economic dispatch. So, before we before I specify the algorithm, we need to keep a couple of things in mind. So, one thing is we need to run consensus on lambda.

and the other thing is P_i is going to be ok. So, we need to ensure this ok. So, this basically gives us the algorithm which is let me first write down the algorithm. So, e generator i it would be running So, \dot{p}_i is going to be given by.

So, let me write this down first and then we will. So, every generator runs this algorithm. So, what is this algorithm? So, essentially \dot{p}_i . So, it is going to be updating its expected dispatch value. So, first of all because we are going to be running consensus on lambda, we do not know lambda to start with.

$$\dot{P}_i(t) = \sum_{j \in \mathcal{N}_i} [\text{sgn}^{\lambda_i}(\lambda_j(t) - \lambda_i(t)) + \text{sgn}^{\lambda_j}(\lambda_j(t) - \lambda_i(t))]$$
$$\dot{\lambda}_i(t) = \dot{P}_i(t) + [\text{sgn}^{\lambda} (P_i - \frac{\lambda - P_i}{2\alpha_i}) + \text{sgn}^{\lambda_j} (P_i - \frac{\lambda - P_i}{2\alpha_i})]$$

So, everyone has their own copy of lambda and correspondingly they will have their own, anyway they will have their own copy of the dispatch value p_i . So, every generator is going to run this algorithm. So, they are going to be updating \dot{p}_i using this expression over here, which we know is very similar to the consensus algorithm. So, if I look at the fixed time consensus algorithm \dot{x}_i in terms of these quantities. I mean there is a negative here because it is x_i minus x_j , there I have written it as x_j minus x_i .

So, you can I mean negative sign is not there, but the right-hand side of this basically ensures consensus on x_i 's right. So, the same algorithm I mean similar kind of consensus algorithm is what I am using over here. Now, for the λ variables right. λ is essentially when what happens if this particular term is equal to 0. So, that means $\lambda_i \dot{p}_i$ is same as $p_i \dot{p}_i$ and if I look at this expression that is what we have $p_i \dot{p}_i$ is same as $\lambda_i \dot{p}_i$ because β is constant.

$$\sum \dot{p}_i(t) = 0 \Rightarrow \sum p_i(t) = \sum p_i(0) = P_{tot}$$

So, if this is equal if this is guaranteed. So, then that means this is going to be satisfied right and if there is consensus on λ that means p_i is also $p_i \dot{p}_i$ becomes 0 ok. So, therefore we have solved the problem right. Is everyone with me on this? So, essentially it is a fixed time consensus kind of scheme both on p_i as well as λ both on this quantity because we want to ensure that everyone goes to. So, this is not a fixed time consensus in the sense that you are not exchanging information with neighbor, but you are ensuring that this I mean this quantity on the right hand side here, this converges to p_i in a fixed time and this is what is happening in this expression.

There is no exchange of information with the neighbors by the way, there is no summation j and i . So, what I am saying is that in a fixed time, I want to ensure that this condition is satisfied. And once this condition is satisfied, then $p_i \dot{p}_i$ is essentially $\lambda_i \dot{p}_i$ over $2\alpha_i$ which is what I want. And once that is true, on top of it, if there is consensus on λ , then $p_i \dot{p}_i$ also becomes 0. And once $p_i \dot{p}_i$ becomes 0, that means we have essentially solved the problem.

I mean the values of conversion, we have solved the problem. So quick few things note here is what is summation $p_i \dot{p}_i$ at any time? This is 0 right because it is an odd function. So if I sum it over from $y=1$ through n and j again 1 through n and a_{ij} and so on. I mean that is something that we had already shown in previous lecture. So this is going to be 0.

So this implies summation $p_i \dot{p}_i$ is always going to be summation $p_i \dot{p}_i(0)$ which is going to be P_{tot} . So, that means, the whatever consensus happens on λ , it would be corresponding to this P_{tot} . And therefore, and it is not just any other random consensus quantity that it is basically we are running the consensus on and therefore, this scheme is going to work. So, now we need to show like basically prove that this entire scheme converges in a fixed time and in order to show that we are first going to show that this converges in a time let us say fixed time T_1 . It takes T_1 time to ensure that this happens. So, once this happens then we would show that in another time T_2 which is greater than T_1 this scheme would also converge.

the top one and then in total time T_1 plus T_2 when you would have the convergence of the entire algorithm. Is it? Yeah, so you are going to be updating two variables at a time. So, let us look at the first one. By the way, what does fixed time convergence result says? Like if you have the Lyapunov inequality satisfied, then there exists a capital time T , some settling time capital T such that trajectories converge before that settling time and then they stay converged for all future times. So, if there is a fixed time convergence that happens here.

So, not only we say that p_i at any like after some capital time T or at times capital T_1 , this is not just p_i is equal to λ_i minus β_i over $2\alpha_i$, but it stays converged for all future times. So, the moment this convergence happens, it is not like when you run the algorithm, you are not going to remove this algorithm at all. I mean, because you want this to stay converged for all future times. So, you will always be updating, even though this may have happened, you would always be updating your λ_i dot over $2\alpha_i$, you will always be running this algorithm. because you want to stay converged for all future times as well and not just instantaneously.

So, this basically scheme which runs on both p_i and λ_i this needs to be run the entire time till you get consensus on λ_i or till you get your p_i 's till you happen to have your p_i 's to converge to a common value or not a common value but to a constant for a given p total. Second is trying to yeah second is trying to ensure this this optimality constraint. So, this is the constraint at optimality right and second second one is trying to in fact in this algorithm what I mean what happens is this this constraint satisfied first followed by the consensus. So, we are going to show we are first going to show that the second ODE equilibrium is reached in a fixed time.

ok. And in order to see this, let me define the error e_i which is going to be the error between p_i minus ok. Is this clear? Right. So, what is e_i dot? It is p_i dot minus λ_i dot over $2\alpha_i$ and if I look at p_i dot minus λ_i dot over $2\alpha_i$ that is nothing but minus of this minus of this quantity right. So, which is going to be negative. and what is the term inside this bracket? It is a e_i .

$$e_i = p_i - \left(\frac{\lambda_i - \beta_i}{2\alpha_i} \right)$$

$$\dot{e}_i = \dot{p}_i - \frac{\dot{\lambda}_i}{2\alpha_i}$$

$$= - \left[\text{sgn}^{p_1} \left(p_i - \frac{\lambda_i - \beta_i}{2\alpha_i} \right) + \text{sgn}^{p_2} \left(p_i - \frac{\lambda_i - \beta_i}{2\alpha_i} \right) \right]$$

So, what do we get? \dot{e}_i is negative. Is this clear? So, now I have to ensure that this e_i goes to 0. and in fact not just this e for a particular i , but for all it is right. So, I need to define a Lyapunov function V which looks something like this. And if this Lyapunov

$$V = \frac{1}{2} \sum_{i=1}^n e_i^2$$

$$\dot{V} = \sum_{i=1}^n e_i \dot{e}_i = - \sum_{i=1}^n e_i \operatorname{sgn}^{\nu_1}(e_i) - \sum_{i=1}^n e_i \operatorname{sgn}^{\nu_2}(e_i)$$

function is 0 only when all e_i 's are 0, otherwise it is going to be positive definite.

So, in order to show that this converges in a fixed time, we need to show that \dot{V} satisfies this inequality that \dot{V} is less than equal to some $c_1 V$ to the alpha $1 - c_2 V$ to the alpha 2 something like that right. So, let us take \dot{V} here and this gives you $e_i \dot{e}_i$ and that is going to be. And what was the definition of the signum function? This new or this signum new kind of this funny looking function. So, if I this is sign like signum μx is essentially x times this quantity right. So, if I multiply if I include if I put let us say substitute e_i for x here.

So, signum $e_i e_i$. So, this would be e_i square times ν norm of e_i . So, e_i square I can write this as e_i square times $e_i \nu - 1$ or $\nu - 1$ rather. So, this becomes $\nu + 1$.

$$\dot{V} = - \sum_{i=1}^n |e_i|^{1+\nu_1} - \sum_{i=1}^n |e_i|^{1+\nu_2}$$

$$= - \sum_{i=1}^n (e_i^2)^{\frac{1+\nu_1}{2}} - \sum_{i=1}^n (e_i^2)^{\frac{1+\nu_2}{2}}$$

$\nu_1 \in (0,1)$ $\nu_2 > 1$
 $\Rightarrow \frac{1+\nu_2}{2} > 1$

e_i is a scalar. So, here, but then you would still have absolute value instead of. So, this becomes \dot{V} is okay. Is this clear? Now, I can write this as Let us say I would rather want to write it in terms of e_i square, because I want to recover my original Lyapunov function. So, this would be e_i square $1 + \nu_1$ by 2 and minus. So, I am almost there except that the summation is outside instead of inside.

Ideally I would want to write this as summation $i = 1$ through n e_i square $1 + \nu_1$ this thing and so on. So, if you assume let us say ν_1 was a number between 0 and 1. So, then $1 + \nu_1$. So, this quantity is also a number between 0 and 1.

This also belongs. And if ν_2 is greater than 1, this implies $1 + \nu_2$ by 2, this is also greater than So, remember if we had looked at one particular result that if z_i 's are positive, z_i is greater than 0, then summation $i=1$ through n , z_i to the power p , this is greater than equal to, if p is a number between 0 and 1. if p is more than 1, then this basically becomes N^{1-p} , if p is greater than 1 right. So, we had already looked at this particular use this particular result in the consensus case. So, we are going to use the same thing over here. Now, this e_i square is here, e_i square is like your z_i right, which are positive numbers and in this case p the power p is basically the exponent p is between 0 and 1.

$$z_i > 0$$

$$\begin{cases} \sum_{i=1}^N z_i^p \geq \left(\sum_{i=1}^N z_i \right)^p & \text{if } p \in (0, 1) \\ \sum_{i=1}^N z_i^p \geq N^{1-p} \left(\sum_{i=1}^N z_i \right)^p & \text{if } p > 1 \end{cases}$$

So, you can use this to essentially approximate it with respect to this and in this case exponent is more than 1. So, you would be able to use this particular result to look at this case right. So, this implies \dot{V} dot is less than equal to ok. And what is this summation e_i square? This is 2 times your Lyapunov function right 2 times V right. So, you get \dot{V} dot is less than equal to negative 2 $V^{1+\mu_1}$ by 2 minus and this is now you have brought this into the familiar way.

$$\Rightarrow \dot{V} \leq - \left(\sum_{i=1}^N e_i^2 \right)^{\frac{1+\mu_1}{2}} - \left(\sum_{i=1}^N e_i^2 \right)^{\frac{1+\mu_2}{2}} N^{1-\frac{1+\mu_2}{2}}$$

$$\Rightarrow \dot{V} \leq - (2V)^{\frac{1+\mu_1}{2}} - N^{\frac{1-\mu_2}{2}} (2V)^{\frac{1+\mu_2}{2}}$$

So, \dot{V} dot is less than equal to some $c_1 V^\alpha$ V to the alpha $1 - c_2 V^\alpha$ V to the alpha 2 and therefore, you can guarantee convergence in fixed time ok. So, that means there exists some time T_1 which is finite such that second ODE converges to its equilibrium in a fixed timeline t less than equal to T_1 . So, that means after time T_1 we know for sure that this constraint is always satisfied or E_i is always 0. Is this clear? So, we know that after time capital T_1 , so this term becomes 0, this term becomes 0 and this derivative is equal to this particular derivative.

So, that is all that we know so far. So, what I can write then is this implies that after time T_1 , we have λ_i dot over 2 alpha i is equal to, is this clear? Why? Because π_i dot is

equal to λ_i dot over $2\alpha_i$ after time capital T 1. So, I can write this. So, this looks like a very familiar consensus update on λ . The only difference is it comes with this coefficient 1 over $2\alpha_i$ which is something that we have not seen. So, we are very quickly going to use the same results, but this time with $2\alpha_i$.

After time T_1 , we have

$$\dot{\lambda}_i = - \sum_{j \in N_i} \left[\text{sgn}^{\alpha_1}(\lambda_i - \lambda_j) + \text{sgn}^{\alpha_2}(\lambda_i - \lambda_j) \right]$$

So, is everyone with me on this that after time T_1 , this is what we are going to obtain. So this is pretty much consensus on λ , something that we had already seen in the previous lecture where we ran consensus on x size right. The only difference is this coefficient 1 over $2\alpha_i$. So therefore, because of this coefficient 1 over $2\alpha_i$, so earlier when we did not have this $2\alpha_i$. what was the consensus value average of the initial ones right.

in this case $\lambda_c = \frac{\Gamma}{N} \sum_{i=1}^N \frac{\lambda_i}{2\alpha_i}$

where, $\Gamma = \frac{1}{\sum_{i=1}^N \frac{1}{2\alpha_i}}$

So, now it is not going to be the average of this it is in fact. So, in this case so we define this λ consensus λ_c that is essentially going to be Γ over N times summation $2\alpha_i$ where Γ is okay. So, this is the this. So, instead of converging to the average, it converges to this particular average of λ is this weighted average, why because, because of this 1 over $2\alpha_i$. And how do we show fixed-time consensus on this or at least convert this to the form that we are familiar with

$$\tilde{\lambda}_i = \lambda_i - \lambda_c$$

$$\dot{\tilde{\lambda}}_i = \dot{\lambda}_i$$

$$V = \frac{1}{2} \sum_{i=1}^N \frac{\tilde{\lambda}_i^2}{2\alpha_i} \rightarrow \dot{V} \leq -c_1 V^{\frac{1+\alpha_1}{2}} - c_2 V^{\frac{1+\alpha_2}{2}}$$

So, we are going to be defining $\tilde{\lambda}_i$ which is going to be λ_i minus this λ_c . So, we know that $\tilde{\lambda}_i$ dot is going to be λ_i dot right that is going to be there for sure. and you can if you just sum it over with 1 over $2\alpha_i$

included, you would show that this is going to be equal to 0. So, this is in fact this is the value that it would converge to. The difference λ_i minus λ_j is going to be same as $\tilde{\lambda}_i$ minus $\tilde{\lambda}_j$ and therefore, you will be able to convert this and the Lyapunov function that you need to choose in this case is that would be $\tilde{\lambda}_i^2$ over $2\alpha_i$. So, with this choice of Lyapunov function, you would be able to follow the proof as it is as we had used in previous lectures and you would be able to show that \dot{V} is less than equal to some $c_1 V$ to the $1 + \mu$ by 2 and therefore, this consensus would happen in a fixed time. So, that this means in a fixed time you are able to. So, let us say this happens in capital T_2 time. So, in time T_1 plus capital T_2 because this scheme is valid only after time T_1 right.

Only after time T_1 this scheme is valid and let us say it takes capital T_2 time to converge. So, in this total time T_1 plus T_2 this algorithm converges. This entire algorithm converges that means you are able to solve the uncapacitated economic dispatch problem in this in a distributed manner in a time capital T_1 plus T_2 . So, this λ is also called I mean it is a dual variable or the Lagrange multiplier, but I mean we have already looked at the interpretation in previous lectures right. It is also called incremental cost variable and there is also popular algorithm called incremental cost consensus algorithm or the ICC algorithm, which is a discrete-time algorithm that is often used to solve uncapacitated economic dispatch problem.

and this is the fixed-time variant of that discrete algorithm. If you have a discrete algorithm, as I said in continuous time you can design much faster algorithms using this novel insights and this is what we have achieved using fixed-time stability. So, λ is also called incremental cost variable. And there is a popular discrete time algorithm or discretized algorithm known as incremental cost consensus or ICC used to solve uncapacitated EDP. Thank you.